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You Read My Mind: Generating and Minimizing Intention Uncertainty Under Different Social Contexts in a Two-Player Online Game

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We investigate an ecologically pertinent form of social uncertainty regarding the ability to read another's intentions. We use classic measures (response time, accuracy) and dynamic measures (mouse trajectories) to investigate how people generate or minimize uncertainty regarding their own intentions under different social contexts, and how uncertainty regarding other's intentions affects decision making. Ninety-six participants ($N = 48$ dyads) completed a two-player online card game, where the goal was to collect cards with a certain feature (e.g., triangles), with participant cursor movements projected to both players. Participants played six games, three cooperatively and three competitively (Social Decision Context). Points were awarded for two decisions: collecting a card matching one's goal (ability to achieve personal goal) and correctly guessing the other player's goal (ability to guess intention). Data revealed: (a) Card scores did not vary with Social Decision Context, (b) Guess scores did vary with Social Decision Context, with more correct guesses when cooperating compared to competing, and (c) Mouse trajectories (durations and mouse distance traveled) decreased when cooperating compared to competing. These results indicate that better guessing during cooperative play is not due to explicit communication (i.e., circling desired cards), but may be due to increased speed and confidence when making decisions in a cooperative context. Additionally, participants could be actively hiding their intention in a competitive context. Thus, social uncertainty when reading another's intentions is both adaptive—affected by the prescribed social context, and automatic—indirectly inferred from the way another moves their mouse when acting with intention.

Public Significance Statement
This line of research uses dynamic and traditional measures in an online, social card game to bridge the gap between the complex and social nature of uncertainty and decision making in real life, and the relatively restricted ways such cognitive processes are traditionally studied in the lab. Results demonstrate the feasibility and importance of using dynamic measures and social tasks, and that social uncertainty regarding another person's goal is projected through movement and can be manipulated depending on social context (i.e., compete vs. cooperate).

Keywords: competition, cooperation, decision making, mouse tracking, social uncertainty

Supplemental materials: https://doi.org/10.1037/xhp0001150.supp

Imagine playing a game of mahjong; with each turn, you pick up a tile and choose whether to keep or toss it. How is such a seemingly simple, dichotomous decision made? You are likely to consider a number of factors, including whether the tile benefits you (does it help build or complete any sets?) or your competitors (do you think they are collecting this tile, and does it potentially nudge them toward a complete set?). Throughout the course of the game, you are also learning by observing your competitors. What decisions are made quickly and confidently; slowly and begrudgingly? What tiles are being tossed out? As the game proceeds, you will likely

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The task and data presented in this study are available on the Open Science Framework (https://osf.io/q8cdv/).
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gain insight into what each player is collecting and what their goals are, which then affects your own behavior and decisions. From this example, it should be clear that this "simple" decision of which tile to keep versus toss is not made in isolation, but influenced strongly by the social environment and the behavior of other individuals. Likewise, there is not a single cognitive process driving behavior, but rather many processes (i.e., decision making, attention, learning). Our goal is to explore how a so-called simple dichotomous decision can be impacted by social uncertainty regarding another's intentions, using measures informed by classic decision making and social uncertainty work (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; Vickers et al., 1972) along with dynamic measures that provide insights into the process of decision making rather than just the outcome (e.g., Chapman et al., 2010, 2015; Song & Nakayama, 2008).

Classic Work on Uncertainty and Decision Making

Decision making and uncertainty are traditionally studied using paradigmatic experiments with static, minimalistic designs, such as go/no-go or forced-choice tasks (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; Vickers et al., 1972). In such tasks, decision uncertainty is created by the experimenters' manipulation of the stimuli. For example, in the classic two-alternative, forced-choice task, participants are shown two stimuli and asked to select one that best matches a criterion (e.g., which of two static patches is more luminous). Experimenters manipulate the similarity between the two stimuli to affect the difficulty of the decision; participants would be more uncertain about the correct choice in a display where two stimuli patches are very similar in luminosity, compared to when one is double the luminosity of the other. Typical results indicate that increasingly difficult decisions, where stimulus uncertainty is high, are reflected in lower accuracy and slower response times (RTs; Ratcliff & Rouder, 1998; Vickers et al., 1972; Wispinski et al., 2020). This paradigm can be adapted to many decision domains including ethical judgments, where participants make life-or-death decisions (e.g., the trolley dilemma; Everett et al., 2016; Skulmowski et al., 2014). Though judgments between luminosity and lives are very different, both use stimulus similarity (50% luminosity vs. 52% luminosity, one man vs. one woman) to drive decision difficulty and consequently uncertainty.

Another method of studying uncertainty incorporates explicit uncertainty or risk into the decisions made. Popularized by the work of Kahneman and Tversky (e.g., Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) these studies present participants with a choice between an uncertain (i.e., 25% chance winning $150) and a certain outcome (i.e., 100% chance of winning $25). Results show an overall pattern of risk aversion between uncertain and certain gains, and risk-seeking between uncertain and certain losses. This work demonstrates that the way uncertainty is framed (60% chance of winning vs. 40% chance of losing) directly affects how people make decisions. While work on perceptual and explicit uncertainty has been informative, this work, by and large, relies on only RT, accuracy, and choice responses as dependent measures, which tend to measure the outcome and not the process of decision making, though some efforts have been made to look at continuous physiological data (de Berker et al., 2016; Greco & Roger, 2003). Additionally, uncertainty here is nonsocial in that the decision is not affected by another person, and under direct experimenter control.

Classic Work on Social Uncertainty and Decision Making

In the real world, uncertainty is often driven by our interpretation of social cues or through our interactions with others. Social uncertainty, conceptualized as uncertainty generated by the states and decisions of others, is often studied using games with feigned dyads and discrete measures, a tradition in decision research and game theory. For instance, the commonly used investment game (Berg et al., 1995; FeldmanHall et al., 2015; Knoch & Nash, 2015; Lamba et al., 2020; Nash et al., 2013) has participants invest a portion of their given money in the other player, whereupon all invested money multiplies in value (i.e., $1.00 invested quadruples to $4.00). The other player then decides how much of the investment to return, thus creating social uncertainty. Studies using this game, and a comparable nonsocial counterpart, highlight the differences between social and nonsocial uncertainty. In social games, participants are not affected by feedback (FeldmanHall et al., 2015) and were biased to invest more in partners who started off as trustworthy and became less reciprocal over time (Lamba et al., 2020). In contrast, nonsocial games demonstrated a greater effect of feedback on investment performance, and less bias in investment, indicating differences between social and nonsocial uncertainty.

While some researchers have attempted to provide a framework for conceptualizing social decision making (FeldmanHall & Shenhav, 2019) and others have used complex computational methods to assess decision making (FeldmanHall et al., 2018; Rusch et al., 2020), the act of studying such complex decision making remains difficult and elusive. Much like its nonsocial relative, research into social uncertainty and decision making relies largely on discrete measures alone (FeldmanHall et al., 2015; Lamba et al., 2020) and feigned participants through some kind of static social representation (photo in FeldmanHall et al., 2015; username in Lamba et al., 2020). Again, such representations and one-shot interactions limit our understanding of complex decisions to a single outcome.

Dynamics as More Revealing of Uncertain Decisions

Exploring decision making as a process rather than an outcome requires the use of time-based measures like movement trajectories (e.g., Chapman et al., 2010; Freeman, 2018; Koop & Johnson, 2013; Song & Nakayama, 2008; Stillman et al., 2020). Often, these kinds of motion studies still employ a forced-choice paradigm, but ask participants to make a rapid reach, usually toward a touchscreen, to indicate their choice. In such paradigms, curved and corrected trajectories typify choices with increased decision difficulty (Chapman et al., 2010; Koop & Johnson, 2013; Song & Nakayama, 2008; Stillman et al., 2020). Rapid-reaching paradigms have also been employed to further investigate classic uncertainty effects like loss or risk aversion but are able to examine behavior as a time-resolved decision-making process (Chapman et al., 2015; Stillman et al., 2020). When responding rapidly, participants produce straighter reach trajectories when deciding between two positively rewarding targets (gain) compared to two negatively rewarding targets (loss), suggesting participants process potential losses more slowly than potential gains (Chapman et al., 2015). Importantly, these findings are not always reflected in RTs or accuracy, demonstrating that motion data can uncover unique information above and beyond classic measures (Chapman et al., 2015; Gallivan et al., 2018; Song & Nakayama, 2008; Wispinski et al., 2020).

Moving Toward Ecologically Valid or Social Tasks

In addition to providing insights into the process of decision making, movement research reflects recent shifts toward greater ecological validity. Increasingly, researchers recognize the importance of understanding human cognition as fundamentally embodied, effected by a person's body and how it moves between contexts and environments (e.g., Foulsham & Lock, 2015; Gobel et al., 2015; Kingstone et al., 2008; Laakasuo et al., 2015; Ma et al., 2023; Risko et al., 2016). As such, more investigations are conducted in enriched environments and/or manipulate facets of the physical and social context to more closely mirror the physical and social complexity of the real world (i.e., Foulsham et al., 2011; Hayward et al., 2017). For example, complex social dynamics can be revealed by studying participant pairs (dyads; e.g., Brennan et al., 2008; Forder & Dyson, 2016; Laakasuo et al., 2015; Newn et al., 2018). In these cases, the effects of social context emerge, such as in partnered visual search which yields faster search RTs when sharing gaze than acting alone (Brennan et al., 2008). These studies demonstrate that what we know from simple, isolationist cognitive tasks changes with increased social complexity. Additionally, even the context or framing of a decision may produce different behaviors. For example, decisions are anticipated to be different when participants are playing an equilibrium game versus playing the same game after learning the other player was given a choice between playing and a guaranteed pay off. This occurs as participants in the second instance can reason the other player will play cooperatively to maximize their payoff above the guaranteed, opt-out amount (van Damme, 1989). Indeed, such research has ignited a push for further research into such context and framing effects (Camerer, 1990). Here we follow the motivation for increased consideration of real social interaction and ecological validity by examining decisions made in participant dyads.

Games as a Happy Medium: Ecologically Valid Task With Experimenter Control

The risk of increasing the complexity and ecological validity by using completely unstructured social interactions is a loss of experimenter control. One way to constrain some of the many complex dimensions at play in a two (or more) person interaction is to embed the interaction in a game, a technique frequently used in decision and social uncertainty research as well as interdisciplinary areas including behavioral game theory (Camerer, 2003; van Dijk & De Dreu, 2021). This affords a level of experimental control over characteristics of the interaction such as the social decision context (i.e., cooperative, competitive) and decisions presented (i.e., controlling or "stacking" the deck to create a balanced experimental design across participant pairs), while allowing research on the dynamic, social, and often unexpected or nonrational behaviors of participants in games.

In game environments, behavioral game theory suggests that much of the uncertainty from other people arises from a lack of rationality and predictability (Camerer, 1990). Such uncertainty can include uncertainty regarding each player's strategy. For example, in games of rock–paper–scissors with computer opponents, participants show uncertainty about their own game strategy by falling victim to suboptimal decision-making heuristics like win-stay, lose-shift rather than the optimal solution of being completely random (Dyson et al., 2016; Forder & Dyson, 2016). In behavioral game theory, Level-*k* reasoning posits that in a game, players can be partitioned into different levels of thinkers depending on their ability to predict the choices of players below them such that Level-0 thinkers follow a simple decision rule, while Level-1 thinkers can predict the decisions of Level-0 thinkers and thus employ those predictions during their decision making, and Level-2 can predict Level-1, and so forth. However, like with rock–paper–scissors, it has been demonstrated that people are not always capable of high-level thinking and decisions never reach the theoretical equilibrium of most advantageous decisions (i.e., random decisions in rock–paper–scissors; Arad & Rubinstein, 2012; Camerer, 2003). Indeed, people instead often engage in myopic and egocentric decision making (Camerer, 2003). In these contexts, while the goal of all players is clear, uncertainty stems from how each player sets out to achieve victory (i.e., their strategy). Social games can also provide uncertainty of motivations, such as when agents choose to act competitively (selfishly) or cooperatively (for the good of all players). This is typified by studies employing the Prisoner's Dilemma, in which participants are asked to cooperate or defect and the number of points earned by each player depends on both their own choice and the other player's choice. Studies again show individuals commonly stray from the optimal tit-for-tat strategy (Axelrod, 1980; Oskamp, 1971), with individual personality traits and cultural characteristics affecting their decisions (Boone et al., 1999; Wong & Hong, 2005). Of note, experiments using rock–paper–scissors or the Prisoner's Dilemma are transparent and symmetrical regarding the participants' intentions—both participants want to win in rock–paper–scissors and earn the maximum number of points in the Prisoner's Dilemma. Additionally, in both cases, players are afforded the same pathway to achieve their goal and are fully aware of this symmetry of intention and opportunity. In contrast, the current study is more like the mahjong example where uncertainty is created precisely because intention is at least initially opaque—players do not know what decisions benefit their opponents.

Given that the communication of intention (or lack thereof) is therefore central to our study, it is important to realize that games can be expanded to incorporate a dynamic representation of the other person. This enables investigations into how intentions can be communicated or hidden. Communication, both verbal and nonverbal, is crucial in social decision making (van Dijk & De Dreu, 2021). We see this in work like that of Newn et al. (2018), who employed an online game (Ticket to Ride) and recorded gaze behavior. When an opponent's gaze was displayed, players self-reported actively using it to predict their opponent's intention. At the same time, when participants were told their gaze would be displayed, they self-reported actively using their gaze to mislead an opponent, highlighting the dual function of gaze in receiving and projecting information (Gobel et al., 2015; Risko et al., 2016). In poker, studies show successful poker players deceive others of their intentions while also taking time trying to read the intention of the other players (Eaves & Nelson, 2014; St. Germain & Tenenbaum, 2011).

The Current Study

As we have discussed, previous work on both nonsocial/social uncertainty and decision making has been very informative and foundational but reveals some gaps. First, the measures and experimental designs used are largely discrete, losing the granularity of the process of decision making. Second, even social uncertainty is explored with limited representations of the other person and their actions. Therefore, we designed a novel, online, two-player reiterative card game which contains dynamic, timeseries measures as well as an active representation of both players to address the current limitations. The design allows us to explore social uncertainty by investigating how social context affects the way people hide or communicate their intentions with motion in real time.

The card game was made of several simple, discrete decisions and played six times, three games competitively and three games cooperatively (counterbalanced blockwise), allowing us to manipulate social decision context through the natural mechanics of the game. Participants earned points by collecting their desired cards (card score) and by correctly guessing the other participant's goal (guess score), therefore encouraging attention to both their own behavior and the other participant's behavior. Since our main motivation was investigating how intention uncertainty was impacted by social decision context, our focus was on potential differences generated from guess scores. Thus, to isolate guess score, we used extensive pilot testing to equate decision difficulty across the social contexts such that the number of available card points across compete and cooperate games was the same. We measured card and guess scores, decision speed through RTs, and motion data with mouse tracking. This combination of measures provides us with the what, when, and where (respectively) of each decision made.

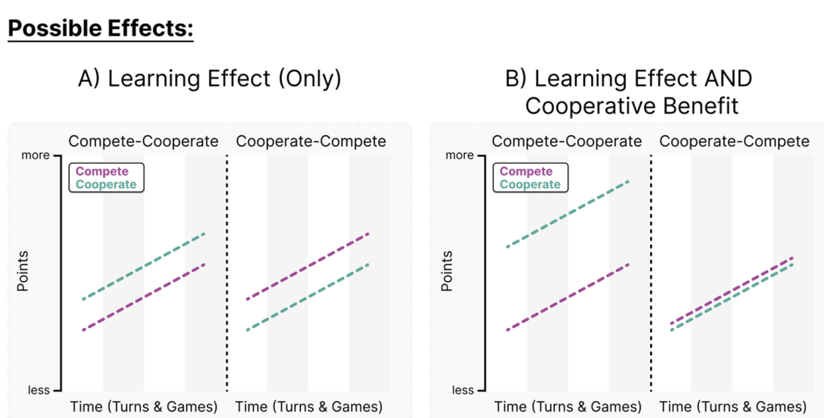
To capture the dynamism and granularity of the predicted effects, we had to use a relatively complicated experimental design with many factors, including social decision context (compete, cooperate), context order (compete first, cooperate first), game (1, 2, 3), turn (1 through 8), and phase, where we split up a turn into smaller time intervals to assess the decision-making portion of each card turn.

Predictions and Expected Data Patterns

First, we anticipate an obligatory learning effect, as learning effects are quite strong and ubiquitous (Crossman, 1959; Stevens & Savin, 1962). Due to the dynamic and reiterative study design, there are three levels at which learning could be expected occur; across turns within a game, across games, as well as across social decision context (by counterbalancing social decision context blockwise, one context will always precede the other). We anticipate that learning will be reflected in guess score increases across some or all of the factors turn, game, or context order. We do not predict any improvement in card scores as we constrained the deck and number of available points.

Second, we anticipate a "cooperative benefit" effect, which we define as an increased ability to guess the other player's goal when playing cooperatively as compared to competitively. This would manifest as higher guess scores in cooperate games as compared to compete games, and is based on prior work revealing an advantage when cooperating (Brennan et al., 2008), and increased guess accuracy when not actively trying to deceive others (Foulsham & Lock, 2015). Finally, the counterbalancing of social decision context creates a confound with context order. Therefore, such an anticipated benefit will emerge as an interaction with the learning effect. If we only found learning effects, then our data would always show an advantage for the second social decision context (Figure 1A). If, however, we see effects of learning and social decision context, then we should observe an additive benefit for those who play cooperative games second (compete first) whereas the learning benefit will appear diminished,

Figure 1
Predicted Patterns of Results



Note. (A) Points across time separated by context order given the presence of only a learning effect. In general, points will improve with time across three possible levels, turn number, game number, and context order. Left panel: Points for those who compete first increase across time. Overall, more points are earned when cooperating. Right panel: Points for those who cooperate first increase across time. Overall, more points are earned when competing. (B) Points across time separated by context order given the presence of a cooperative benefit effect in addition to a learning effect. In general, points will increase with time. Left panel: Points for those who compete first increase across time. Overall, more points are earned when cooperating. This difference is greater than with a learning effect alone due to the additive nature of the learning and cooperative benefit effects. Right panel: Points for those who cooperate first increase across time. Points earned are not different when competing compared to cooperating. This difference is diminished with the cancellation effect of learning (helps compete performance) and the cooperative benefit effect (helps cooperative performance). See the online article for the color version of this figure.

eliminated or even reversed for those who play compete games second (cooperate first; Figure 1B).

Third, based on prior trajectory tracking work (Chapman et al., 2010, 2015; Song & Nakayama, 2008), we expected decision time and movement patterns to track changes in social decision context. Previous literature has shown longer RTs and less direct movements to indicate harder decisions and containing less information for an observer trying to infer intention (Chapman et al., 2010, 2015; Song & Nakayama, 2008). However, the social nature of the experiment task means that participants may also attempt to communicate by moving their mouse more (i.e., drawing symbols). Therefore, due to the novel and social aspect of the task, we do not have a predicted direction or size of the effect. We include effect sizes in our results to facilitate future power analyses using this, or a similar task. Importantly, the continuous nature of the measure and design consequently means that key moments in the decision arise in certain phases of the turn above others (i.e., when the card information becomes available). Therefore, we specifically anticipate differences in the phases within a turn that are crucial to the decisions. Specifically, as shown in Figure 2, there are key parts of a trial when all decision information is first made available. We expect our dynamic measures of decision making to show a social decision context difference during these key time periods, but not before or well after the decision information is available (see Figure 2 for breakdown and definitions of phases within a turn).

Method

Transparency and Openness

Reported data, the task used, as well as research materials (i.e., participant instructions) are posted publicly and accessible on Open Science Framework (https://osf.io/q8cdv/). Data were processed and analyzed using MATLAB (The MathWorks, Natick, Massachusetts, United States), JAMOVI (Şahin & Aybek, 2020), and custom MATLAB software Gaze and Movement Analysis (GaMA; Williams et al., 2019). Due to the continuous nature of the data, there are multiple barriers to posting the raw data including file size and possible lack of anonymity related to biometric data. Instead, we have posted the entire processed data set for all measures used. This study and analyses were not preregistered as the study was exploratory in nature.

Participants

The data reported were collected from 2021 to 2022. One hundred seventy-five participants accessed our consent form. However, due to the difficulty of testing online, where two people had to join the task at the same time and have a stable internet connection for approximately 110 min, only 96 participants (65 female, 27 male, four nonbinary/prefer not to answer; $M_{\text{age}} = 19.72$, $SD = 2.54$) grouped into 48 pairs successfully completed the study. Previous work on dynamic measures suggests a minimum of 40 participants to obtain adequate power, and as such we aimed to collect over 40 dyads (Gallivan & Chapman, 2014). All experimental procedures were approved by the University of Alberta's Research Ethics Office (Pro00100812). Informed consent was obtained from all individual participants included in the study. Participants were recruited through the university's undergraduate research participation pool and were awarded course credit for their participation. Participants had the opportunity to earn a $5 bonus based on their performance. The participation pool was used as this study was too complex and unsuitable for data collection via other common online methods such as Amazon mTurk and Prolific. As such, results may not generalize to all populations (i.e., older adults, individuals without post-secondary education).

Platform and Procedure

The study was implemented using Labvanced, an online experimental platform that allows for two participants to synchronously interact with each other using their personal devices (Finger et al., 2017). Participants were instructed to complete the study in a quiet environment, with minimal distractions. Participation was restricted to the use of a laptop or desktop with a Chrome browser.

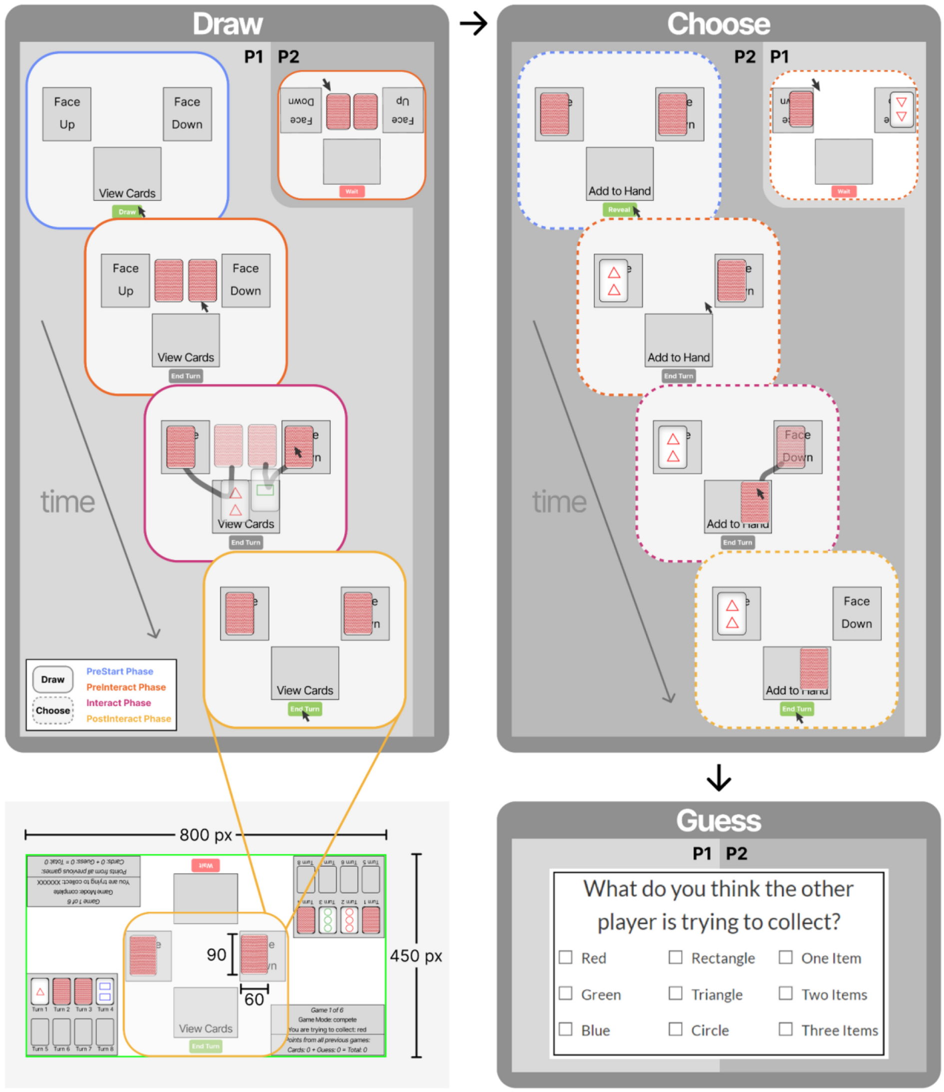
Participants began in a virtual lobby where they waited for a second participant. Once both participants were online, a button appeared, allowing them to commence the study. Participants first completed a short series of demographic questions and were then led through comprehensive and thorough instructions and instructive videos (see online supplemental materials for links to the online task and instruction videos). Participants then played six rounds (games) of a simple card game consisting of eight turns each. Their goal in each game was to earn points by collecting cards of a certain type and by guessing what kind of cards the other player was trying to collect.

Design

The simple card game used 27 unique cards, with the cards varying on three dimensions (color, shape, number). Each of these dimensions contained three variations (i.e., red, green, blue). At the level of the game, we manipulated the social decision context (compete or cooperate) by changing the point system (see below for the specific details on how points were awarded). In the competitive context, each participant earned points individually. Only the participant with the highest score at the end of that game kept their points, while the participant with less points received zero points. In the case of a tie, both players received 0 points. In the cooperative context, if the total number of points earned at the end of the game was >160, participants earned an average of the two participants' points (e.g., if players earned 170 points, each of them was awarded 85 points for that game). Otherwise, both participants received zero points. The cutoff of 160 points was selected based on pilot performance to balance the number of points awarded in the compete and cooperate games. Each participant played the game six times, with a block of three competitive games and a block of three cooperative games (block order counterbalanced). Each game was made up of eight turns and on each turn each player ended up with one card. Crucially, participants were able to view the other player's mouse movements in real time throughout the games. Each participants' goal was to collect the highest number of points possible. Every game, participants were given a goal which remained the same across the eight turns within that game (i.e., collect red) and each card they collected with that characteristic was worth 10 points. Participants' goals were never on the same dimension (see Figure S1 in the online supplemental materials, for a breakdown of all decision types and potential points earned each turn). At the end of each turn, participants were asked to guess their fellow player's goal ("What do you think the other player is trying to collect?," see Figure 2, guess panel). Each correct guess was also

Figure 2

Procedure for One Turn in a Game



Note. Sample fifth turn shown. Each turn is made of two discrete decisions: A draw decision (draw panel, top left) and a choose decision (choose panel, top right). During the draw decision, Player 1 (P1, light background) is active and draws two cards by clicking the draw button (draw-PreStart, blue border [first illustrated screen]; draw decisions = solid borders), causing two face down cards to appear. Using their mouse (arrow cursor), P1 can click on (draw-PreInteract, orange border [second screen]) and drag each of the cards. P1 can see the face of each card by dragging it to the view cards area. P1 decides which cards Player 2 (P2, dark background) will see as face-up and face-down by dragging one card into each of those areas (draw-Interact, magenta border [third screen]). P1 ends the draw decision by clicking the end turn button (draw-PostInteract, yellow border [last screen]). During the choose decision, P2 is active and reveals the face-up card by clicking the reveal button (choose-PreStart, choose decisions = dashed borders). P2 then clicks and drags the cards (choose-PreInteract) to decide which card to add to their hand and which to give to P1 (leaving a card in face up or down area; choose-Interact). P2 ends the turn for both players by clicking the end turn button (choose-PostInteract). After each turn, P1 and P2 are asked to guess what cards the other player is trying to collect (guess panel, bottom right). Bottom left panel shows the active player's full-screen layout (800 × 450 pixels, scaled to each user's screen) and the relative size of a card (60 × 90 pixels). Insets in the top right of the draw and choose panels represent what the inactive player (e.g., P2 during draw, P1 during choose) sees during those decisions: a rotated representation of the screen, a wait indicator, and the real-time position of the active player's mouse position. See the online article for the color version of this figure.

worth 10 points (note, explicit feedback regarding points earned from cards and guesses in a particular game was only provided at the end of that game; online supplemental materials: end of game—turn summary screen). Participants were motivated to collect points by an extra incentive—if they (as an individual) earned more than 200 points by the end of the study, they were awarded a $5 gift card (64.6% of participants received this bonus). At the start of each game, players were shown a screen summarizing the game information, including what game number they were starting, what social decision context they were in, how many points they needed to unlock the bonus and what their and the other player's current score was (see the online supplemental materials for a sample start game screen).

During each turn, two discrete decisions occurred (see Figure 2). The first decision (i.e., the draw decision) began when one participant (Participant 1; P1) drew two cards by clicking the "draw" button (Figure 2, draw panel, PreStart phase). During the draw decision, the face of the card was only ever visible to P1 when they dragged a card into the "view cards" area (Figure 2, draw panel, Interact phase). P1 then decided which card to present to the other player face up (by dragging a card into the "face up" area), and which card to present face down (by dragging a card into the "face down" area), locking in their decision by pressing the "end turn" button (Figure 2, draw panel, PostInteract phase). For P1, the "end turn" button could only be clicked (lit up green) if one card was in each of the face up and face down areas, otherwise it was inactive (colored gray). The second decision (i.e., the choose decision) began when the other participant (Participant 2; P2) first revealed the face up and face down cards by clicking the "reveal" button (Figure 2, choose panel, PreStart phase). P2 then selected which of the presented cards (one face up, one face down) to add to their hand (by dragging one card into the "add to hand" area), and which card to give to P1 (whichever card remained in the "face up" or "face down" area; Figure 2, choose panel, Interact phase). P2 locked in their decision by clicking the "end turn" button (Figure 2, choose panel, PostInteract phase). P2 could move the cards freely until this point; however, the cards remained in their orientation the whole time (e.g., the choosing player could not look at the face of the face-down card). After clicking "end turn," P2 would then be able to view the face of the face-down card if they had selected it, but they would not be able to change their decision. For P2, the "end turn" button could only be clicked (lit up green) if one card was in the "add to hand" area and the other was in either the "face up" or "face down" areas, otherwise it was inactive (colored gray).

Across turns, P1 and P2 alternated drawing and choosing cards, and across games, the start player (P1) alternated. Thus, each participant was drawer and chooser four times per game and was the drawer first for three games, meaning each participant experienced each role 24 times in the study. During each turn, each player was only the "active" player for one of the decisions, either draw or choose. When active, their screen was highlighted with a green border and the shared text "face up," "face down," "view cards/ add to hand" and button text ("draw," "reveal," "end turn") were oriented upright for them (see Figure 2, bottom left panel, full-screen display). The active player's mouse position was visible to them as an upright arrow cursor and could be used to interact with the cards. When a player was inactive, they were able to watch the other player's mouse movements but could not control anything on the screen (their mouse cursor was hidden and inactive). The inactive player's screen was not highlighted and the shared text was inverted (Figure 2, top-right inset in draw and choose panels). a red "wait" text box appeared in the correct orientation at the bottom of their screen. The inactive player could watch the active player's mouse movements as the position of the active cursor was shown in an inverted orientation to mirror what the active player was doing.

Both players could always see a text box in the lower right of their screen summarizing what game number and social decision context they were playing (Figure 2, bottom left panel, full-screen display). This box also reminded them of their goal, which was visible only to them. Finally, it also summarized how many points they had earned from previous games (note, no information about the current game was presented). At the end of the choose decision, both players were made active and went to a guess screen (Figure 2, guess panel) to make their guess about what type of cards they thought the other player was trying to collect. Mouse cursor position on these screens was not shared between participants.

On each turn, each player, therefore, received one card, either face up or face down. As turns progressed, acquired cards were represented to players in the lower left of their screen and the cards of the other player were visible in an inverted card-set in the top right of their screen (Figure 2, bottom left panel, full-screen display). Any time a player was active (including on the guess screen) they could click on a face-down card from their collection in the lower-left and the face of the card would be shown to only them. Face-up cards were always visible to both players.

After each game, players were both made active and shown a summary of their performance across three screens (see the online supplemental materials). First, a screen provided visual feedback (green check marks or red "X"'s) for each of their card and guess scores for that game. A next button allowed them to advance to a second summary screen showing their current game score as well as their score across all completed games. Finally, another next button allowed them to advance to a screen where they used a slider to judge how well they thought the other player played the last game (*extremely poorly* to *extremely well*) and how well they thought the other player played competitively/cooperatively (*not at all* to *perfectly*). After this screen they could advance to the next game, or, if all six games were complete, participants would proceed to the end of the experiment where they saw a screen indicating if they had successfully earned the bonus (see the online supplemental materials). Before exiting the experiment, each player completed the autism spectrum quotient (Baron-Cohen et al., 2001) and the competitive orientation measure (Newby & Klein, 2014) to address different research questions which are not discussed here. Participants also entered some information about their computer, internet browser, and strategies/feedback before exiting the experiment.

Dependent Measures

Discrete data collected once per turn included each players' card score (getting a card that matched their goal) and each players' guess score (correctly guessing their opponent's goal). Our primary motivation was to see if the social decision context (compete vs. cooperate) impacted these scores and, if so, how this was reflected in the timeseries measures.

Continuous or timeseries data included mouse coordinates, each frame transition, each time the mouse entered and exited the areas of interest on the screen, each time the mouse started dragging (clicked and moving) and stopped dragging a card, and each time a card entered each of the relevant areas on the screen. Timeseries data were resampled to 60 Hz using a custom MATLAB script which linearly filled in gaps between existing data points. Resampled timeseries data were fed into our custom GaMA software run in MATLAB (for an example project using GaMA; see Williams et al., 2019), which allows the mouse to be visualized and analyzed alongside the task-relevant objects and events (e.g., the cards; where and when they enter the various key interaction zones; when the draw and choose decisions begin and end; see Figure 2).

In GaMA, the draw and choose decisions were split into four phases (see Figure 2): (a) PreStart was defined as the time between the beginning of the trial (when the first frame is shown) and when the participants clicked the button to commence their action ("draw" in the draw decision; "reveal" in the choose decision). (b) PreInteract was defined as the time from the end of the PreStart phase to the first time a player clicked on (e.g., interacted with) a card. (c) Interact was the time in which the participant was interacting with the cards and spanned from the end of the PreInteract phase until the last time they stopped dragging (clicked on and moving) any card. (d) PostInteract was defined as the period of time between the end of the Interact phase until the participant clicked the "end turn" button, at which point their turn was concluded and the turn was either passed to the choose player (if they had been drawing) or the turn ended for both players (had they been choosing). For each phase, we defined two dependent measures: duration (time in seconds) and mouse distance traveled (cumulative distance across all phase time points in Labvanced-scaled pixels; total screen was 800×450, see Figure 2, lower left panel). As discussed above, we anticipate the greatest social decision context differences in these measures to arise in phases key to the decision-making process. Specifically, for the draw decision this will be the PreInteract phase (when both cards become available), but largely the Interact phase (when card face information becomes available). For the choose decision, this will be the PreInteract phase (when card face information becomes available) and the Interact phase.

Results

For card and guess scores, we employed a $2 \times 3 \times 8 \times 2$ mixed-effects analysis of variance (ANOVA) with social decision context (compete, cooperate), game number (1, 2, 3), and turn number (1 through 8) as within-subjects factors, and context order (compete first, cooperate first) as the between-subjects factor. For duration and mouse distance traveled, we first split the data by role (draw or choose), and then conducted a $2 \times 3 \times 4 \times 4 \times 2$ mixed-effects ANOVA with social decision context (compete, cooperate), game number (1, 2, 3), turn number (1 through 4, as each person only draws four times and chooses four times per game) and phase (PreStart, PreInteract, Interact, PostInteract) as within-subjects factors, and context order (compete first, cooperate first) as the between-subjects factor. For all analyses, all trials were included, regardless of whether or not points were earned.

Our primary focus was to determine if the social decision context impacted player performance and behavior. As such, from each of our mixed ANOVAs, we exclusively report the highest-order significant interaction(s) (or, if no interactions, then the main effect) involving unique factors plus the factor of social decision context. In cases where we report an interaction with social decision context, we perform follow-up ANOVAs using the following hierarchy: we first split by context order, followed by phase, then game number, and finally social decision context at each turn number. Greenhouse–Geisser corrections were applied when relevant, and Bonferroni corrections were applied to any reported post hoc comparisons.

Effects and interactions from these ANOVAs not involving social decision context are reported in the online supplemental materials.

Performance Analyses

Card Scores

If our predictions are correct and our extensive piloting was effective, we would not expect to see any interaction including the key factors social decision context, context order, turn number, and/or game number. The ANOVA for card scores returned no main effects or interactions with social decision context (all $F\text{s} < 2.1$, $p\text{s} > .1$, see Figure 3, left panel), suggesting that participants were equally good at winning points from cards that matched their goals regardless of whether they cooperated or competed. This also suggests we were successful in balancing the number of points available across the social decision contexts.

Guess Scores

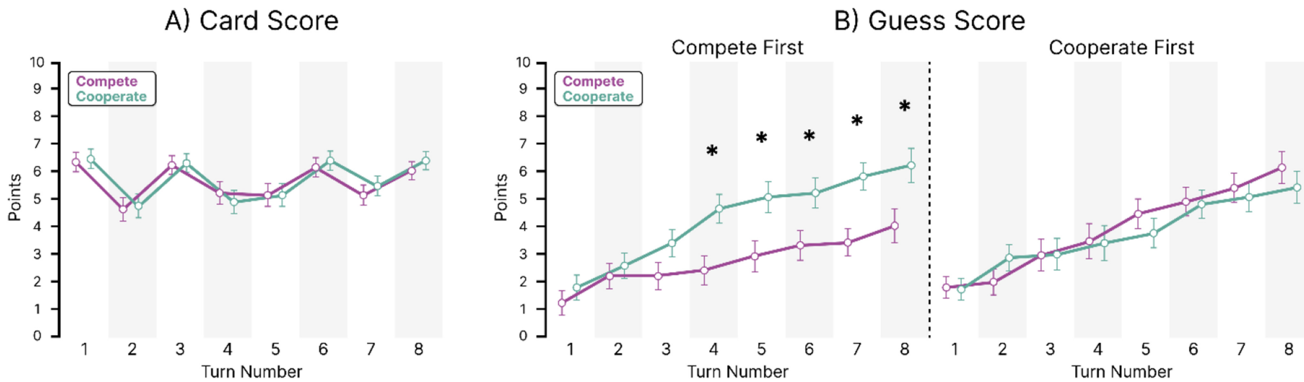
If our predictions are correct and guess scores show both a learning effect and a cooperative benefit (see Figure 1B), we expect to see an interaction between social decision context and some/all of the factors marking time: context order, turn number, and/or game number. For the ANOVA with guess scores, the highest-order interaction with social decision context was a three-way interaction between social decision context, context order, and turn number, $F(5.99, 563.34) = 3.69$, $p < .001$, $\eta_p^2 = .038$, followed up below.

Splitting by context order (compete first, cooperate first), we ran two separate 2×8 (Social Decision Context $\times$ Turn Number) repeated measures ANOVAs (Figure 3B). As predicted, for those who competed first (Figure 3B, left panel), the data revealed a two-way interaction between social decision context and turn number, $F(5.55, 260.68) = 3.38$, $p = .004$, $\eta_p^2 = .067$, in that when cooperating, participants were better at guessing the other player's goal. To determine which specific turns show the benefit for those who cooperate, we ran Bonferroni-corrected t-tests comparing guess scores at each turn, as a function of social decision context, and found that participants scored higher when cooperating from Turn 4 to Turn 8 (all $t\text{s} > 3.39$, all $p\text{s} \leq .001$, $d \geq .049$).

In contrast, for those who cooperated first (Figure 3B, right panel), the data only revealed a main effect for turn number, $F(5.07, 238.48) = 37.75$, $p < .001$, $\eta_p^2 = .445$, and no interactions, suggesting that regardless of whether participants were cooperating or competing, their guess score improved across turns.

This pattern of results confirms our hypotheses of both a learning effect, which increases performance across turn number and context order, and a cooperative benefit effect which sees increased performance for cooperate games. Therefore, when you compete second (cooperate first) these effects cancel each other out, but when you cooperate second (compete first), these effects are additive. Overall, this pattern of findings suggests that participants who were cooperating were more successfully sharing goal intentions than those who were competing.

Figure 3
Card and Guess Scores Across Turns



Note. (A) Card score across turn. No significant differences in card score for social decision context (cooperate—teal/lighter lines, compete—purple/darker lines). Error bars show 95% CI of the difference between compete and cooperate at each turn. (B) Guess score across turn, separated by context order. In general, guess scores increase across turns. Left panel: Participants in the compete-first context order who were cooperating achieved higher guess scores on later turns than those who were competing. Right panel: Participants in the cooperate-first context order have similar guess scores across all turns, regardless of social decision context. Error bars show 95% CI of the difference between compete and cooperate for each context order at each turn. See the online article for the color version of this figure.

Draw Decision Durations

The ANOVA for draw decision durations (Figure 4A) revealed two highest-order (three-way) interactions involving Social Decision Context: Social Decision Context × Game Number × Context Order, $F(1.87, 175.31) = 8.9$, $p < .001$, $\eta_p^2 = .086$, and Social Decision Context × Phase × Turn Number, $F(3.93, 369.82) = 3.06$, $p = .017$, $\eta_p^2 = .032$.

For the first interaction, we split by context order and ran two separate 2 × 3 (Social Decision Context × Game Number) repeated measures ANOVAs. For those who competed first (Figure 4A, left panel), we found two main effects and a two-way interaction between social decision context and game number, $F(1.92, 90.30) = 4.16$, $p = .020$, $\eta_p^2 = .081$, in that when competing, participants spent more time each game, however, they sped up more quickly across games than when cooperating, Game 1: $t(47) = 6.76$, $p < .001$, $d = .976$; Game 2: $t(47) = 5.17$, $p < .001$, $d = .746$; Game 3: $t(47) = 4.92$, $p < .001$, $d = .710$. Conversely, for those who cooperated first (Figure 4A, right panel), we found a main effect and an interaction between social decision context and game number, $F(1.68, 79.19) = 4.89$, $p = .014$, $\eta_p^2 = .094$, as participants were slower when cooperating, especially in Game 1; however, none of the time post hoc comparisons survived Bonferroni correction, Game 1: $t(47) = 2.23$, $p = .030$; Games 2 and 3, $ts < 1$, $ps > .4$.

Thus, and counter to the notion that learning just makes you faster, we found that during draw decisions, participants who competed first spent considerably more time when competing as compared to cooperating across all three games (Figure 4A, left panel), whereas participants who cooperated first only showed a numerical difference in duration across social decision context for the first game (Figure 4B, right panel). This suggests that players learn to take longer when competing (during cooperate first/compete second), possibly as a tool to mask their goal intentions, thus accounting for the relatively long and game-invariant times for this group.

For the second three-way interaction (Social Decision Context × Phase × Turn Number), we split the data by phase and ran four separate 2 × 4 (Social Decision Context × Turn Number) repeated measures ANOVAs. As predicted, the only phase to yield any significant effects with social decision context was the Interact phase, yielding both a main effect of social decision context as well as an interaction between social decision context and turn number, $F(2.43, 230.95) = 3.43$, $p = .026$.

Following up, we analyzed each social decision context separately and found a significant effect of turn number when participants competed, $F(2.39, 227.48) = 7.29$, $p < .001$, $\eta_p^2 = .071$, but not when they cooperated ($F < 3$, $p > .08$), suggesting that cooperate players were specifically faster during the Interact phase while drawing cards.

Choose Decision Durations

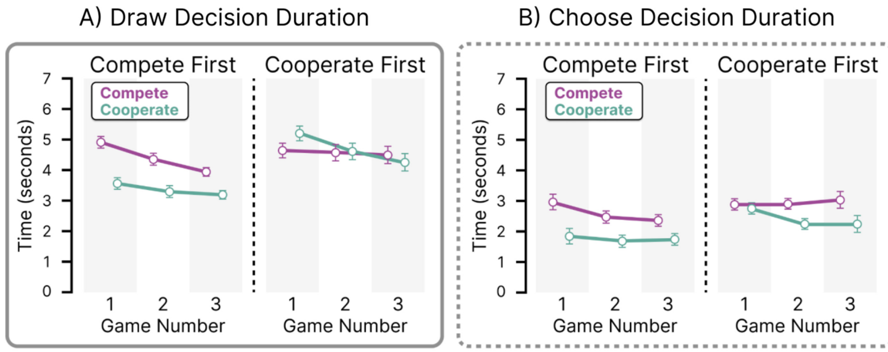
For the ANOVA with choose decision durations (Figure 4B), there were two highest-order interactions involving social decision context; a four-way interaction between social decision context, game number, turn number, and context order, $F(4.04, 379.60) = 2.44$, $p = .046$, $\eta_p^2 = .025$, and a two-way interaction between social decision context and phase, $F(2.06, 193.64) = 15.65$, $p < .001$, $\eta_p^2 = .143$.

For the four-way interaction, we split the data by context order and ran two 2 × 3 × 4 (Social Decision Context × Game Number × Turn Number) repeated measures ANOVAs. For those who competed first, we found an interaction between social decision context and turn number, $F(1.88, 88.57) = 3.20$, $p = .048$, $\eta_p^2 = .064$, whereby competing was much slower for turn 1 than cooperating was, and that difference in duration was reduced by turn 4, regardless of game number ($ts < 4.43$, $p < .009$, $d > .402$).

For those who cooperated first, we also found an interaction between social decision context and game number, $F(1.72, 80.78) = 3.92$, $p = .029$, $\eta_p^2 = .077$; follow-up analyses show that there was no effect of social decision context for Game 1, $t(47) < .3$, $p > .7$, however, participants were faster when cooperating as compared to competing for Games 2 and 3, Game 2: $t(47) = 3.16$, $p = .003$, $d = .0439$; Game 3: $t(47) = 2.62$, $p = .012$, $d = .3786$ (Figure 4B, right panel).

Figure 4

Draw and Choose Decision Durations



Note. (A) Draw and (B) choose decision durations across game number, separated by context order. In general, decisions are made more quickly in later games. (A) Left panel: Participants in the compete-first context order who were cooperating (teal/lighter lines) took less time making draw decisions than those who were competing (purple/darker lines). Right panel: Participants in the cooperate-first context order took about the same time making draw decisions, regardless of social decision context (see manuscript for full details). (B) Left panel: Participants in the compete-first context order who were cooperating took less time making choose decisions than those who were competing. Right panel: Participants in the cooperate-first context order also took less time making choose decisions when cooperating versus competing, except in Game 1. In all panels, error bars show 95% CI of the difference between compete and cooperate for each context order at each game number. See the online article for the color version of this figure.

For the two-way interaction between social decision context and phase, we ran Bonferroni-corrected *t*-tests at each phase, comparing performance between cooperate and compete. Results showed longer durations in the PreInteract, $t(95) = 5.58$, $p < .001$, $d = .57$, and Interact phases for compete games compared to cooperate games, $t(95) = 3.35$, $p = .001$, $d = .34$, other *t*s < 1, *p*s > .3, again supporting our prediction that key decision moments are not equally distributed across a decision. Thus, participants were slower to make decisions specifically in the phases of the task where all decision information was available and decision making occurred.

In sum, during choose decisions participants who competed first spent considerably more time choosing when competing compared to cooperating across all turns, whereas participants who cooperated first were only slower when competing as compared to cooperating for Games 2 and 3. This violates a pure learning effect account of the data, which would lead to "cooperate-first" individuals responding consistently slower when cooperating than competing at the level of turn number or game number. Instead, the data supports the existence of an additional cooperative benefit effect. Further, the slower responses occurred specifically for the PreInteract and Interact phases where decision making is occurring, potentially demonstrating increased difficulty when choosing cards in a competitive situation.

Draw Decision Mouse Distance

The ANOVA for mouse distance traveled during draw decisions returned two interactions that satisfied our criteria: a three-way interaction between social decision context, phase and context order, $F(1.58, 148.51) = 5.76$, $p = .007$, $\eta_p^2 = .058$, and a two-way interaction between social decision context and game number, $F(1.77, 166.71) = 4.14$, $p = .02$, $\eta_p^2 = .042$; see Figure 5 draw panel for a heatmap of mouse dwell times.

For the three-way interaction, we split the data by context order and ran two 2 × 4 (Social Decision Context × Phase) repeated measures ANOVAs. For those who competed first, there was a main effect of social decision context, $F(1, 47) = 4.87$, $p = .032$, $\eta_p^2 = .094$, with greater mouse distances traveled during compete ($M = 992$) as compared to cooperate ($M = 951$) games. For those who cooperated first, there were no effects involving social decision context (*F*s < 3.5, *p*s > .05), violating a pure learning account.

For the two-way interaction between social decision context and game number, we ran Bonferroni-corrected *t*-tests at each game number, comparing performance between compete and cooperate. While there was a general trend for compete to have decreasing distance across all three games while cooperate did not change, none of the post hoc comparisons of compete versus cooperate reached significance for any single game (all *t*s < 2, *p* > .05).

Again, we interpret the draw decision mouse distance results as the interaction of two factors—moving your mouse more efficiently with experience (whatever you do second; learning effect) and moving your mouse less when cooperating as compared to competing (cooperative benefit effect).

Choose Decision Mouse Distance

The ANOVA for mouse distance traveled during choose decisions returned two interactions that satisfied our criteria: a four-way interaction between social decision context, game number, turn number, and context order, $F(4.68, 435.11) = 3.12$, $p = .011$, $\eta_p^2 = .032$, and a three-way interaction between social decision context, phase, and context order, $F(2.52, 234.70) = 5.40$, $p = .002$, $\eta_p^2 = .055$; see Figure 5 choose panel for a heatmap of mouse dwell times. For the four-way interaction we split by context order and ran two 2 × 3 × 4 (Social Decision Context × Game Number × Turn Number) repeated measures ANOVAs. For those who competed first, we found a main effect of social decision context, $F(1, 47) = 5.15$, $p = .028$, $\eta_p^2 = .099$, as participants moved their mouse more when competing ($M = 703$) as compared to cooperating ($M = 642$). For those who cooperated

Figure 5

Difference of Compete Versus Cooperate Mouse Dwell Time

Note. (Compete–cooperate) mouse dwell time for draw decisions (left panel) and choose decisions (right panel) broken across phase. Dwell time reflects the average amount of time the active player's mouse cursor was at a particular location as a difference between the compete and cooperate contexts. In all phases, there is evidence that participants spend longer and move their mouse over more of the screen when competing than cooperating (compete > cooperate, purple (greyscale) tones). This is particularly pronounced in phases where decision information has been revealed, but the decision is not finalized. These include the draw-interact (magenta [third screen] solid border), choose-PreInteract (orange [second screen] dashed border), and choose-Interact (magenta [third screen] dashed border) phases. Notably, we see no evidence of more mouse dwell time when cooperating (cooperate > compete, teal tones, none found). See the online article for the color version of this figure.

first, there were no significant effects with social decision context (all Fs < 2.5, $ps > .09$).

For the three-way interaction between social decision context, phase and context order, we split by context order and ran two 2×4 (Social Decision Context × Phase) repeated measures ANOVAs. For those who competed first, we found two main effects and an interaction between social decision context and phase, $F(2.38, 111.79) = 4.49$, $p = .009$, $\eta_p^2 = .087$. Following up, we ran Bonferroni-corrected t-tests at each phase, comparing performance between compete and cooperate. Results showed greater mouse distances traveled in the PreStart, $t(47) = 4.03$, $p < .001$, $d = .5811$, and Interact phases for compete games compared to cooperate games when competing first, $t(47) = 2.90$, $p = .006$, $d = .4190$, other $ts < 1.55$, $ps > .13$.

For those who cooperated first, we found one main effect and an interaction between social decision context and phase, $F(2.72, 127.63) = 5.12$, $p = .003$, $\eta_p^2 = .098$. Following up, we ran Bonferroni-corrected t-tests at each phase, comparing performance between compete and cooperate. While there was a general trend for cooperate to show shorter mouse distances traveled in the PreInteract phase, none of the post hoc comparisons reached significance for any single phase ($ts < 2.23$, $ps > .03$).

In general, the mouse distance data when making choose decisions follows the pattern of most of our measures where participants became more efficient with experience and were more efficient when cooperating as compared to competing.

Discussion

Our study aimed to investigate social uncertainty arising from not knowing another person's intentions. We explored this kind of intention uncertainty by manipulating social context (competition vs. cooperation) in a simple two-player online card game where participants scored points for getting the right card and for making the right guess about the other player's goal. We used both conventional measures (e.g., decisions made) as well as dynamic measures (decision time across phases, mouse trajectories), and overall found (a) no difference in card scores across social decision context, (b) differences in guess scores, whereby you are better at guessing your opponents' goal when cooperating (i.e., cooperative benefit effect) and with more task experience (i.e., learning effect), and (c) when competing, participants take longer to make decisions and move their mouse more (i.e., cooperative benefit effect). This occurs particularly in phases which are key to the decision-making process. Primarily, the Interact phase for the draw decision during which the card information becomes available (cards dragged to view zone) and a decision can be made, and the PreInteract and Interact phase for the choose decision, as card information becomes available after clicking the "reveal" button and does not require interaction. Taken together, it is clear that varying social decision context successfully changed the degree to which players were able to communicate their intentions—when cooperating, players made more decisive decisions (less time and less mouse distance) and were able to more successfully guess the intentions of the other player. This pattern was in spite of also observing typical learning effects.

The fact that the card scores were not different across social decision context provides assurance that our game design was balanced across our key manipulation. In contrast, our data reveal that, as predicted, participants achieved higher guess scores when cooperating as compared to competing even though the study design emphasized the benefit of attending to the other player in both social decision contexts. This guess benefit also interacted with task experience, as participants had higher guess scores in the second block of games. Higher scores for the second social decision context are expected due to participants learning the mechanics of the game and becoming more efficient with their guess strategies. The results regarding a cooperative benefit dovetail with previous work showing better performance in cognitive tasks when cooperating (Bahrami et al., 2012; Brennan et al., 2008), a tendency toward decisions which promote fairness and cooperation (Camerer, 2003; Knez & Camerer, 1995), and heavier consideration of harm to others compared to harm to self when making decisions (Crockett et al., 2014). Thus, demonstrating that participants are more effective at sharing their intentions when cooperating is perhaps not surprising. What is surprising is that they were able to do so given the impoverished channels for communication available in this experiment—the only way they could share information was via what they chose and how they moved their mouse to choose it. But, as we just described, participants did not differ in their ability to score points for their own cards, thus ruling out the "what" as a likely source of useful information. Therefore, the only avenue for manipulating social uncertainty was simple mouse movements. With the inclusion of dynamic data, we were additionally able to address how mouse dynamics disambiguates the intention uncertainty in this task.

Mouse movements could give rise to the guess-score-benefit when cooperating in at least two ways: (a) participants are explicitly signaling their goals, such as circling the desired cards or traits. This would lead to longer phase durations when cooperating and more mouse movements. Or, (b) participants are implicitly signaling their intentions by quickly moving to take cards that they want. This would lead to shorter phase durations when cooperating and fewer mouse movements. Our duration and mouse distance result definitively support (b), the idea of implicit communication of intention when dyads were cooperating. First, we find reduced decision durations when dyads were cooperating, mirroring the cooperative benefit of basic cognitive tasks such as visual search in reducing RT (Brennan et al., 2008). Second, this study aligns with previous work demonstrating that decision information is available when watching how people choose to make a decision (Pesquita et al., 2016). In this previous work, a participant's ability to use movement information from observing another person reach fell below conscious awareness. The idea that decision information is implicit and reliant on a representation of motion is buttressed by behavioral game theory work which shows that individuals tend to have a myopic view of decision making (difficulty predicting the choices of others and even self) when given little to no representation of another person (Camerer, 1990). Third, myriad studies with hand (Chapman et al., 2010; Song & Nakayama, 2008) and mouse (Freeman et al., 2011) tracking have indicated that easier decisions are reflected in faster, and straighter trajectories. Our study builds on this general finding to suggest that the movements generated when making easier decisions are also more likely to convey information about the intention of the movement.

Importantly, there is also another form of communication that is likely at play in our experiment. In addition to cooperative decisions yielding implicit sharing of intention, it is likely that when competing, participants are hiding their intention. Here, spending more time making decisions and moving the mouse less efficiently when competing successfully generates intention uncertainty and hides a player's goals. This aligns with observational work demonstrating a poker player's focus on deceiving others of their intention (Eaves & Nelson, 2014; St. Germain & Tenenbaum, 2011). While it is difficult to parse out the degree to which our duration and mouse-traveled differences due to social context are from implicit-cooperative communication or deliberate-competitive miscommunication, one result points to contributions from the latter. Specifically, in most cases in this experiment, decisions got easier over time such that the games completed in the second social context block were completed more quickly and with fewer mouse movements. A notable exception to this experience effect was the duration result for the group that competed second (i.e., see Figure 4B, cooperate first). Unlike the experience account would predict, this group spent more time making decisions in their later, compete, games. One interpretation of this result is that players were learning to delay their movements as a means of creating goal uncertainty. This finding supports previous research into deception that demonstrates people will manipulate nonverbal signals to deceive. For example, when participants' gaze positions were observed while they performed a preference task honestly or while trying to deceive, observers were worse at guessing preference for deceptive compared to honest trials (Foulsham & Lock, 2015). Further, analysis of participant eye behavior showed their distribution across options was more even when being deceptive (Foulsham & Lock, 2015). Another group analyzed mouse movements and found concealing intention during an online questionnaire resulted in slower cursor movements (Jenkins et al., 2019). In both cases, it appears that observed gaze/movement is a useful channel for conveying or concealing intention. In our study, participants may themselves be generating a degree of uncertainty with their mouse, which intuitively aligns with past research demonstrating that people often take advantage of uncertainty to decrease prosocial or "fair" decisions (Dana et al., 2007; Haisley & Weber, 2010; Kappes et al., 2018). The competitive social decision context and the constrained social representation of the mouse may combine to create an atmosphere of ambiguity and anonymity which allows participants to engage in this uncertainty generation.

Further iterations of this work will need to be designed to disentangle the cooperate-communicate from the compete-conceal of intention. One possibility would be the inclusion of a nonsocial control, in which a single participant picks between two cards to gain points. The nonsocial RTs and trajectories can then be compared to both cooperate and compete games. If compete and nonsocial dependent variables were not significantly different, we could deduce that cooperating leads to better signaling of intention. In contrast, if cooperate and nonsocial DVs were not significantly different, we could deduce that participants are hiding their intentions when competing.

Overall, this work has demonstrated that people will spontaneously change their movements under different social decision contexts and that these differences in movement generate (when competing) or minimize (when cooperating) intention uncertainty. This type of uncertainty only arose in this task because there were two interacting players who did not know each other's game goals. Importantly, this dyadic interplay with partial information captures a form of uncertainty frequently encountered in the real world but rarely studied in the laboratory. That is, the complexity and uncertainty of a social decision comes not only from the choices of the decision itself, but also from attempting to understand and possibly influence the cognitive process of other people. This type of uncertainty extends well beyond simple games and is prevalent in numerous daily decisions. For example, when deciding whether to hold a door for an oncoming pedestrian, there is uncertainty as to whether their intention is to use the door, head in a different direction, or would prefer to open the door themselves.

This study also makes important methodological contributions, demonstrating that even in an era of "social distancing" you can use new online resources (Finger et al., 2017) to create a social task with pairs or groups of participants interacting in real time while physically separate and using their own digital devices. Moreover, you are not restricted to discrete measures of performance, but can learn a great deal about social decisions by analyzing the evolution of movement responses that enact them. This suggests that future work should incorporate the measurement and broadcasting of gaze; another nonverbal signal which receives and produces social information, communicating intention or deception beyond verbal signals (Buller & Aune, 1987; Ekman & Friesen, 1969; Gobel et al., 2015; Risko et al., 2016).

Another advantage of moving to remote data collection is that it opens up the possibility of testing an increasingly diverse population, no longer restricting testing to traditional undergraduate students (see Prather et al., 2022 for excellent reasons to test diverse populations). This is crucial in social cognition research where work has demonstrated the importance of personal characteristics and individual history on many facets of cognition. For example, work has shown that females are better at decoding nonverbal cues than males (Hall, 1978), individuals with a higher number of autism traits respond less to social stimuli (Hayward & Ristic, 2017; Moriuchi et al., 2017), including cues derived from movement (Pesquita et al., 2016), and Chinese cultural priming increases cooperation among friends in the Prisoner's Dilemma compared to American priming (Wong & Hong, 2005).

While taking advantage of remote data collection can expand the scope of the populations you can explore, there are equally important future studies to be conducted with physically present individuals. Persistent representations of the other player via a cursor icon is a poor proxy for their physical presence. Indeed, some research shows that differing levels of social presence either physically or virtually can influence decision making to be more cooperative or individualistic (Bos et al., 2002; Rocco, 1998). We are therefore looking forward to implementing an in-person version of the current study with 3D eye and motion tracking to continue the line of research showing how physical context can affect cognition (Bos et al., 2002; Hayward et al., 2017) and test whether our online findings will translate to an in-person setting.

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