The Role of Predictability in Cooperative and Competitive Joint Action

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RUNNING HEAD: ROLE OF PREDICTABILITY

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Abstract

Predictability may be an important component of cooperative action, or it may arise as a by-product of involuntary entrainment with another's behavior. Further, differences previously observed in cooperative versus competitive actions may represent a fundamental distinction between behaviors with opposite goals, or they may simply reflect the output of different physical actions. The role of predictability in cooperative versus competitive behavior was directly tested using a joint sequential button-pressing task in which P1 pressed their key followed by P2 pressing their own key. In the cooperative condition, both actors shared the goal of minimizing P2's reaction times. In the competitive condition, P1 tried to maximize P2's reaction times, whereas P2 continued to try to minimize them. It was found that P1 was much more predictable in the timing of their presses in the cooperative condition than in the competitive condition, and this coincided with faster P2 responses when cooperating than when competing. A second experiment showed the effects of the predictability of P1's responses on the speed of P2 responses were similar when P1 was replaced by a schematic hand, showing they could not have been due to the transmission of subtle nonverbal cues by P1. These results demonstrate that being predictable is an important strategy in the timing of cooperative joint action whereas being unpredictable is an important strategy in competition, and that they have opposite effects on a co-actor's ability to respond quickly.

The Role of Predictability in Cooperative and Competitive Joint Action

Much recent work on joint action has examined the motor processes underlying cooperative behaviour (e.g., Konvalinka, Vuust, Roepstroff, & Frith, 2010; Vesper, van der Well, Knoblich, & Sebanz, 2011, 2013; Ramenzoni, Davis, Riley, Shockely, & Baker, 2011). Other research has looked into the structure of competitive actions (Capozzi, Becchio, Garbarini, Savazzi, & Pia, 2015; Georgiou, Becchio, Glover, & Castiello, 2007; Meerhoff, & De Poel, 2013), and some has even compared cooperation to competition (Capozzi et al., 2015; Georgiou et al.). Here, we show for the first time how an identical joint action game is approached when played in either cooperative or competitive modes.

One theme that has emerged in studies of cooperative joint action is predictability (Glowinski et al., 2013; Konvalinka et al., 2010; Sebanz & Knoblich, 2009; Vesper et al., 2011, 2013; Yin et al., 2016). Researchers have argued that when two or more actors cooperate towards a common aim, they adapt their behavior so as to be more predictable to a partner. For example, Vesper et al. (2011) examined the timing of button presses in pairs that were instructed to cooperate in order to achieve presses that coincided as nearly as possible. Vesper et al. showed not only that actors had less variable response times, i.e., became more predictable, when performing in a joint context relative to performing alone, but that lower variance correlated with improved performance when participants actively cooperated. In another study, Glowinski et al. (2013) examined the movements of performers in a string quartet, and observed that the timing of non-performance-related movements (e.g., head movements) became more systematic when performing as a part of a group rather than when performing alone.

Although results such as these imply that being predictable is an important, indeed crucial, contributor to the coordination of cooperative actions, there are alternative explanations for the changes in timing that have been observed. Specifically, at least some of the reported changes in timing may reflect an artefact of the social nature of the situation rather than an explicit strategy used to improve joint performance. For example, participants may involuntarily imitate the timing of their co-actors, a phenomenon known as entrainment (e.g., Richardson, Marsh, Isenhower, Goodman, & Schmidt, 2007; Romero, Kallen, Riley, & Richardson, 2015), or may speed up their performance and reduce its variability due to social facilitation (Aiello & Douthitt, 2001; Zajonc, 1965). As such, apparent increases in predictability in cooperative actions may often represent nothing more than a natural response to performing in a social context.

One previous study directly compared cooperation to competition (Georgiou et al., 2007). Here, kinematics were recorded while pairs of participants moved a block from a starting position near their body to a target position halfway between themselves and their partner. In the cooperation condition, participants tried to join their blocks together as quickly as possible. In the competition condition, participants competed in order to place their block in a target area first. Results showed that the timing of kinematic markers such as peak acceleration and peak velocity was much more coordinated when pairs were cooperating than when they were competing. However, although this study avoided a potential confound with the numbers of actors, it did require distinct behaviors in the cooperation and the competition conditions. Thus, one cannot exclude the possibility that the differing tasks themselves may have contributed to the kinematic changes observed in the opposing conditions.

Here, we sought to address some of the shortcomings noted above by constructing a game which, rather than varying whether or not a single or multiple actors took part (e.g., Glowinski et al., 2013) or varying the behavior under cooperative vs. competitive conditions (Georgiou et al., 2007), used a single task with two actors that differed only in terms of the goals of each participant in the cooperative and competitive variants. Pairs of actors sat across from each other at a table on which was set a computer keyboard. At the sounding of a tone, P1 pressed a key, followed by P2. In the cooperative condition, both P1 and P2 had the same goal of minimizing P2’s reaction times. In the competitive condition, the actors were given opposing goals: Here P1 was instructed to try to maximize P2’s reaction times, whereas P2 continued to try to minimize them.

By this method, we hoped to provide a clear demonstration of the role of predictability (and its opposite, unpredictability) in cooperative and competitive joint actions. Based on previous research, we expected predictability to be used as a tactic by P1 in the cooperative version of the game. In the competitive version, Game Theory holds that a strategy of being unpredictable would have the best outcome for P1 (Fundenberg & Tirole, 1991). Thus, we expected P1 to use qualitatively opposite strategies in the two versions of the game, and for these strategies to significantly affect the performance of P2.

Experiment 1

Methods

Participants. Sixty-eight participants were recruited from the campus of Royal Holloway University of London and took part in exchange for a small chocolate reward. All participants were right-handed by self-report, and all had normal or corrected-to-normal vision and no motor or neurological impairments. Participants were assigned to 34 pairs at random. The study was approved by the Department of Psychology Ethics Committee at Royal Holloway.

Apparatus. The study took place in a quiet room, at a 120 cm by 80 cm table at which the participants were seated facing one another. On the table, halfway between the participants, sat a computer keyboard onto which the numbers ‘1’ and ‘2’ had been written on paper and taped over the ‘l’ and ‘d’ keys, respectively. The keys to be pressed by each participant (‘l’ for P1 and ‘d’ for P2) were each 40 cm in front of and 7 cm to the right of the respective participant’s midline. A computer program produced a tone to signal the onset of each trial, and also recorded the timing of button presses for analysis offline.

Procedure. Participants began each trial with their right index finger resting gently on their respective keys. Participants were instructed to neither speak nor move any part of their body other than this finger on each trial. At the sounding of the tone, participants were required to press their keys in sequence, P1 first followed by P2. In the cooperation condition, participants were instructed that the aim of both was that P2’s presses occurred as soon after P1’s as possible, and that P1 should try to facilitate P2’s task. In the competition condition, participants were informed that P2 had to press their button as soon after P1 as possible, but that P1 was to do their best to hinder P2’s performance, within the bounds of the rules (i.e., no verbalizations or movements other than pressing the key). No hints or instructions were given as to how each actor might best accomplish their respective goals in either condition. There was no explicit limit on the latency of P1’s responses; they could take as little or as much time as they wanted to press their button on any given trial. The experimenter monitored each participant to ensure they followed instructions. On a given trial, an error was score if either participant pressed their button out of turn or moved part of the body apart from the responding finger. Prior to their first block in the role of P1 or P2 (the first and third blocks), participants were given a few practice trials to ensure they understood the task and what was required.

Design and Analysis. Each participant played each role (P1 and P2) in both a cooperative and competitive condition, for a total of four blocks of trials. The order of blocks was counterbalanced across pairs. There were 15 trials in each of the four blocks for a total of 60 trials per pair. Response time was recorded for each press of both participants. For P1, the response time was recorded as the time elapsed between the onset of the tone and P1's press. For P2, the response time was recorded as the time elapsed between P1's press and P2's press.

To construct an index of the predictability of P1 responses, we generated an empirical approximation of the hazard function, that is, the likelihood of a response at each millisecond given that a response had not yet occurred. The hazard function represents the predictability of P1's responses from P2's point of view at any given instance. That is, at any point in time (until P1 responds), P2 knows that the P1 response has not yet occurred and would be interested in how likely it would be to occur imminently. Presumably, if he or she knows it were imminent (i.e., a high hazard rate) they would be better able to prepare a rapid response. This measure has been termed conditional probability by Niemi and Näätänen (1981) who note that it is a powerful predictor of response time in studies of the effects of foreperiod on simple reaction time.

Quartiles were calculated for each participant's responses in each condition, dividing the distribution of responses into four bins. The probability of a response within each millisecond within a bin was then estimated as the probability of a response in the bin (.25) divided by the millisecond bin width. These probabilities were converted to (conditional) hazard rates by dividing by the probability that a response had not occurred in a lower bin. The conditional probabilities of a response at each millisecond were changed into an information-theoretic index of predictability by taking the log (to the base 2) and changing the sign (i.e., $h = -\log_2 p$ where h is information and p probability; e.g., Shannon & Weaver, 1949). A related analysis of foreperiod was used by Klemmer (1957) and Nickerson and Burnham (1969), but applied on a block-by-block basis. The probability index can be understood as the reduction in uncertainty of a response at any given millisecond in each participant's distribution of responses. Less predictable responses will convey higher information because greater uncertainty about P1's response has been reduced. For each bin in P1's response distribution, we calculated the median P2 response time.

We eschewed the use of null hypothesis significance testing because of the many well-known problems with this technique (e.g., Cohen, 1994; Dixon & O'Reilly, 1999; Wagenmakers, 2007). Instead, in order to quantify the evidence for different possible interpretations of the results, we compared the suitability of different models using likelihood ratios. This ratio indicates how likely the data are given one model (and its best parameter estimates) relative to how likely the data are given a second model (and its best parameter estimates). As described by Glover and Dixon (2004) and others, if the data from an independent groups design are normally distributed, the likelihood ratio can be written as $\lambda = (SSE_1 / SSE_2)^{n/2}$, where SSE_1 and SSE_2 are the residual sum of squares in the two models (see also Masson, 2011). Such likelihood ratios will always favor models with more parameters. Consequently, according to the suggestion of Glover and Dixon, we adjusted for the varying number of parameters based on the Akaike Information Criterion (AIC; Akaike, 1973). The adjusted likelihood ratio can then be written as $\lambda_{adj} = \exp((AIC_1 - AIC_2)/2)$, where AIC_1 and AIC_2 are the AIC values of the two models. Such likelihood ratios have been termed evidence ratios by Burnham and Anderson (2002). Thus, assessing evidence based on adjusted likelihood ratios is tantamount to model selection based on AIC values, a common model selection criterion. By way of comparison, an attained significance level of .05 in some prototypical hypothesis testing situations corresponds to an adjusted likelihood ratio of approximately 3. The models were fit with the program lmer (Bates, Maechler, Bolker, & Walker, 2015) running in the R statistical environment (R Core Team, 2016). For each model, we also report a marginal R^2 value (that treats random effects as error), calculated using the methods of Johnson (2014) and Nakagawa and Schielzeth (2013) using the program r.squaredGLMM from the MuMIn package (Bartoń, 2016).

Results

Two pairs of participants were excluded for failure to follow the instructions. Of the remaining 32 pairs, 5.1% of trials in the cooperative condition and 3.9% of the trials in the competitive condition were scored as errors and removed from subsequent analysis. Means, standard deviations, and coefficient of variation for P1 and P2 in the cooperation and competition conditions are reported in Table 1. In order to provide evidence for overall differences in P1 reaction time, we compared two linear mixed-effects models, one with an effect of condition (R^2 = .094) and a null model. The former was substantially better, λ_{adj} > 1000. We also performed the same comparison for P2 reaction times. In this case, the model with an effect of condition (R^2 = .022) was substantially better than the null model, λ_{adj} > 93.96. In these models, the effect of condition was assumed to vary across participants.

The distribution of P1 responses in the cooperative and competitive conditions is shown in Figure 1. These histogram were constructed by averaging the quartiles across subjects and then calculating the frequency from the fact that 25% of the responses fall between each quartile. As can be seen, P1 responses in the cooperative condition are relatively short, with a narrow, fairly symmetric distribution. In contrast, responses in the competition condition are much more spread out with a pronounced skew.

Table 1

Mean, standard deviation, and coefficient of variation of reaction times for P1 and P2 in the cooperation and competition conditions in Experiment 1.

	Mean (ms)	Standard Deviation (ms)	Coefficient of Variation
P1			
Cooperation	1134	312	0.273
Competition	2968	2575	0.836
P2			
Cooperation	199	64	0.327
Competition	232	69	0.272

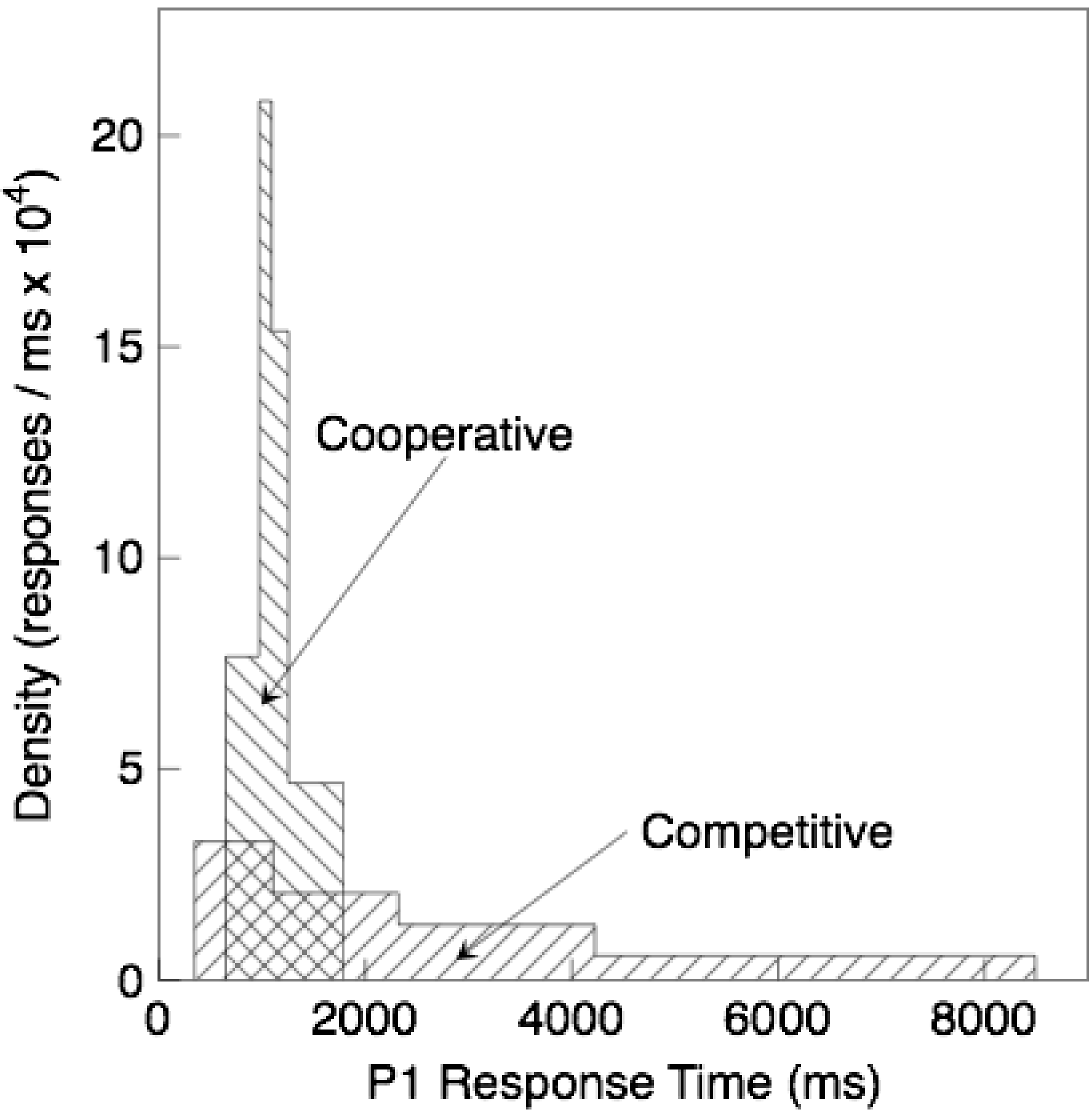

Figure 1. Distribution of P1 response times in the cooperative and competitive conditions, estimated by averaging the quartiles over subjects.

Figure 2 shows the median P2 responses as a function of predictability (i.e., information) for each P1 response bin. Two features of the data are evident. First, P1 generated more predictable responses in the cooperation condition than in the competition condition: The mean information was 7.92 bits (se = 0.06) in the cooperative condition and 10.72 bits (se = 0.06) in the competitive condition. Indeed, there was relatively little overlap in the two distributions. In order to quantify the evidence for this difference, we fit two linear mixed-effects models, one that included an effect of condition (R^2 = .455) and a null model without the effect of condition. In this instance, the comparison indicated overwhelming evidence in favor of the model that included the effect of condition, $\lambda_{adj} > 1000$. As before, the effect of condition was assumed to vary across participants.

The second result apparent in Figure 2 is that P2 response time increased with information; that is, P2 was slower the less predictable the P1 response was. Although response times were slower in the competitive condition, the effect appeared to be due simply to the concomitant change in information. As before, we assessed the evidence for this effect by fitting linear mixed-effects models. The effect of information was assumed to vary across participants. A model that included the effect of information (R^2 = .071) was substantially better than a null model, $\lambda_{adj} > 1000$. There was no evidence that also including the effect of condition (R^2 = .070) was any better, $\lambda_{adj} = 0.38$. Further, although a model with just an effect of condition (R^2 = .005) was better than the null model, $\lambda_{adj} > 1000$, there was substantial evidence that the model that included both the effect of condition and information was better still, $\lambda_{adj} > 1000$. This pattern of results implies that the effect of condition was mediated entirely by information.

As a further assessment of the effect of informativeness of individual P1 responses, we decomposed the effect of information into two components: the average information for each participant and the deviation from each participant's mean. A model that included both components (R^2 = .064) was substantially better than a model with only the subject averages (R^2 = .006), $\lambda_{adj} > 1000$. This result implies that the effect of informativeness on P2 reaction time operated at the level of individual responses, not merely the overall distribution of P1 reaction times.

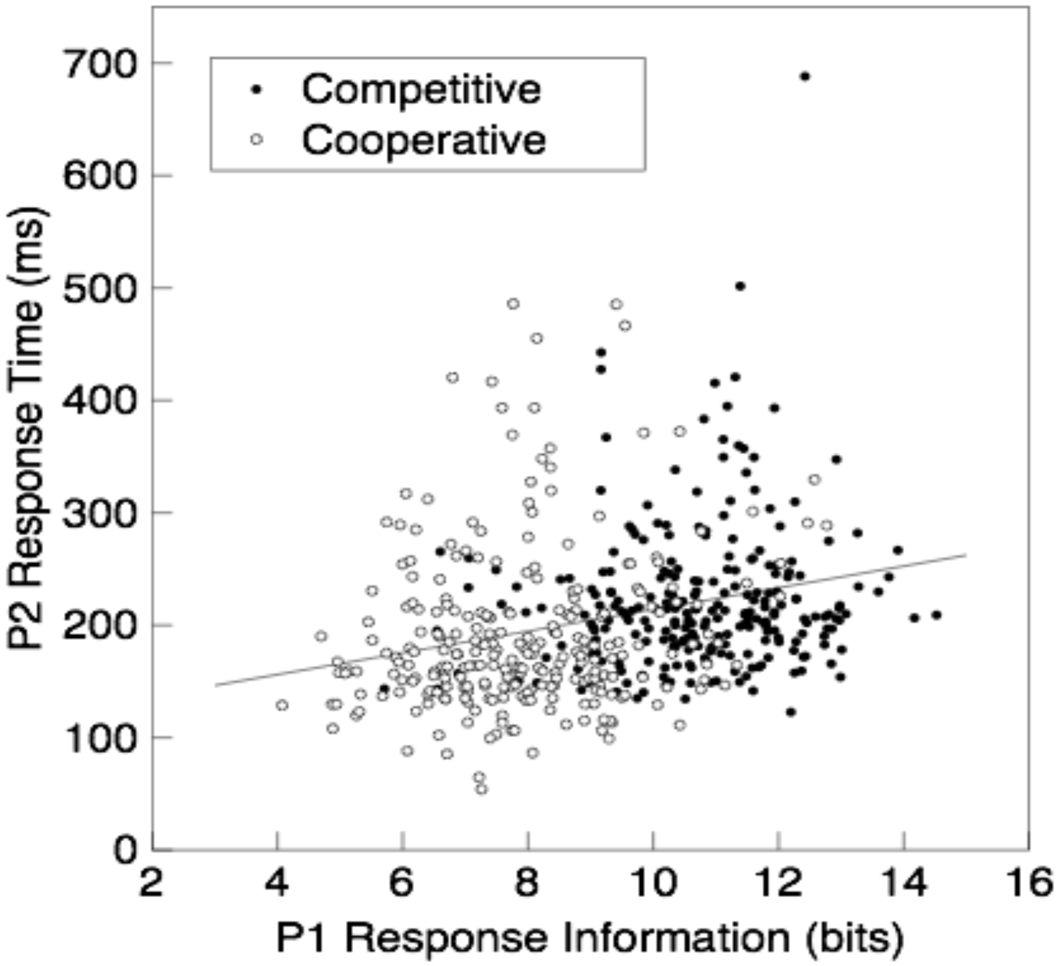

Figure 2. Median P2 response time (after removing the random effects of subject) as a function of the information in P1 responses, calculated from an empirical estimate of the P1 hazard function. The linear function represents the parameter estimates (i.e., the intercept and slope of the information effect) from the model fit.

The hazard rate is related to the mean and standard deviation of the response time distributions. In particular, if the distribution is generally more spread out and skewed (as in the competitive condition as depicted in Figure 1), the hazard rate is lower and the transmitted information will be higher. However, statistics such as the mean and standard deviation are properties of the entire distribution rather than individual (albeit in our case, binned) responses. In order to assess whether the mean and the standard deviation contributed any further variance over and above information, we averaged the information and the P2 responses within each condition and subject. The effects of information on P2 responses were much as before: A model with simply the effect of information (R^2 = .109) was substantially better than the null model, λ_{adj} > 1000, and a model that added the effect of condition (R^2 = .122) was no better, λ_{adj} = 0.62. Critically, the model with the effect of information was not improved by adding the effect of mean P1 response time (R^2 = .112), λ_{adj} = 0.57, the effect of P1 standard deviation (R^2 = .109), λ_{adj} = 0.37, or both (R^2 = .122), λ_{adj} = 0.26. In contrast, models that also included the effect of information were better than those included only the mean response time (R^2 = .056), λ_{adj} = 572.76, just the effect of standard deviation, (R^2 = .048), λ_{adj} = 602.33, or both (R^2 = .055), λ_{adj} = 648.86. From these analyses, we conclude that informativeness of each individual subject's distribution was a better predictor of P2 reaction time than other aggregate statistics.

Discussion

The results of Experiment 1 provided clear evidence that participants altered their behavior depending on the social context in which the task was performed, and in spite of the task being otherwise identical. Moreover, the results show the predicted qualitative difference in behavior of P1 inasmuch as the predictability of their action as modeled by the information provided to P2 differed strikingly depending on whether they were cooperating or competing. In the cooperation condition, P1 tended towards more predictable responses, whereas in the competition condition, P1 became much more unpredictable. This is clear evidence that cooperative and competitive behaviors employ opposing strategies.

These opposing strategies had obvious effects on the performance of P2. In the cooperation condition, when P1 was being more predictable, P2's reaction times were shorter, and in the competition condition, P1's unpredictability led to longer reaction times in P2. Both of these results were best explained as a function of the information inherent in P1's responses.

One interesting aspect of the results was the length of the mean reaction times of P1 in the cooperation condition (1134 msec). It might be argued that having shorter reaction times by consistently pressing the button as quickly as possible would make it easier for P1 to maintain a more predictable response. One possibility is the observed reaction times reflected a desire by P1 to ensure that P2 was set and prepared to respond. Another is that P1 preferred to use a timing strategy that required less vigilance than responding as quickly as possible would have. Regardless of the reason for these seemingly large response times on the part of P1 in the cooperation condition, they were still notably faster than the response times in the competition condition.

Experiment 2

Although our instructions to both participants required that they only move their finger and not provide any other cues to their partner, it is possible that some other, subtle nonverbal cues were used by P1 to either assist or deceive P2 in either the cooperation or competition condition, respectively. If this were the case, it would not necessarily discount our explanation that P1 used predictability when being cooperative and unpredictability when being competitive. However, it could complicate our interpretation that the differences in the timing of P1's responses in the two conditions were the paramount means by which these strategies were enacted. Another question is to what extent the social context of the task might have affected P2's responses. In past studies, the presence of another has been shown to reduce response timing and variability (Aiello & Bouthitt, 2001; Vesper et al., 2011; Zajonc, 1965). In order to control for these factors, we conducted a second experiment in which the timing of P1's responses was yoked to those in Experiment 1. Here, P1 was replaced by a schematic finger, and P2 performed the task in isolation.

Method

Participants. Sixty-four University of Alberta undergraduates performed a simple response-time task similar to the P2 task in Experiment 1. Some of these participants received a small monetary compensation while the balance received course credit. All participants had normal or corrected vision, and all were naive as to the exact purpose of the experiment. The study was approved by the University of Alberta Research Ethics Board.

Apparatus. The study took place in a quiet room. Participants sat alone approximately 50 cm from computer screen with a keyboard placed at a comfortable distance. On the screen appeared a schematic depiction of an index finger near a button. In terms of visual angle, the depiction was approximately 5˚ vertically by 2˚ horizontally.

Procedure. Participants began each trial with their right hand resting comfortably on the space bar. At the beginning of each trial, a brief tone was presented over headphones. After a variable foreperiod, the "go" signal was presented in which the schematic finger pressed the button (which turned blue). Participants responded as quickly as they could after the "go" signal by pressing the spacebar. An error message was presented if they pressed prior to the "go" signal.

Participants began with a block of five practice trials with a constant foreperiod of 750 ms. This was followed by two blocks of trials, with the duration of the foreperiod yoked to the sequence of P1 response times from Experiment 1. (Only trials with correct responses were included.) A block of trials was introduced with the message, "In this block, the computer will try to make it easy/hard to respond quickly" depending on whether the foreperiods corresponded to the cooperative or competitive task, respectively. The order of the two tasks matched that used in Experiment 1.

Data Analysis. Data were analyzed as in Experiment 1, with the obvious exception that only one participant took part in each trial. As before, the effect of information was assumed to vary across participants.

Results

Summary statistics are shown in Table 2. The overall error rate was 3.3% in the cooperative condition and 2.7% in the competitive condition; these trials were excluded. As in Experiment 1, response time in the cooperative condition was faster than that in the competitive condition. In particular, a model that included an effect of condition (R^2 = .048) was better than the null model, $\lambda_{adj} > 1000$.

As shown in Figure 3, the effect of the informativeness of the (yoked) P1 responses on P2 response times was very similar to that obtained in Experiment 1. Similar to Experiment 1, a model with informativeness (R^2 = .104) was substantially better than the null model, $\lambda_{adj} > 1000$, and better than a model that included the effect of condition (R^2 =

.047), λ_{adj} = 380.1. However, a model that included both information and condition (R^2 = .103) was better than the model with just the effect of information, λ_{adj} = 6.80, suggesting that in this experiment, our measure of informativeness did not predict all of the systematic variation in response times.

Table 2.

Mean, standard deviation, and coefficient of variation of reaction times in the cooperation and competition conditions in Experiment 2.

	Mean (ms)	Standard Deviation (ms)	Coefficient of Variation
P2			
Cooperation	310	48	0.153
Competition	346	64	0.185

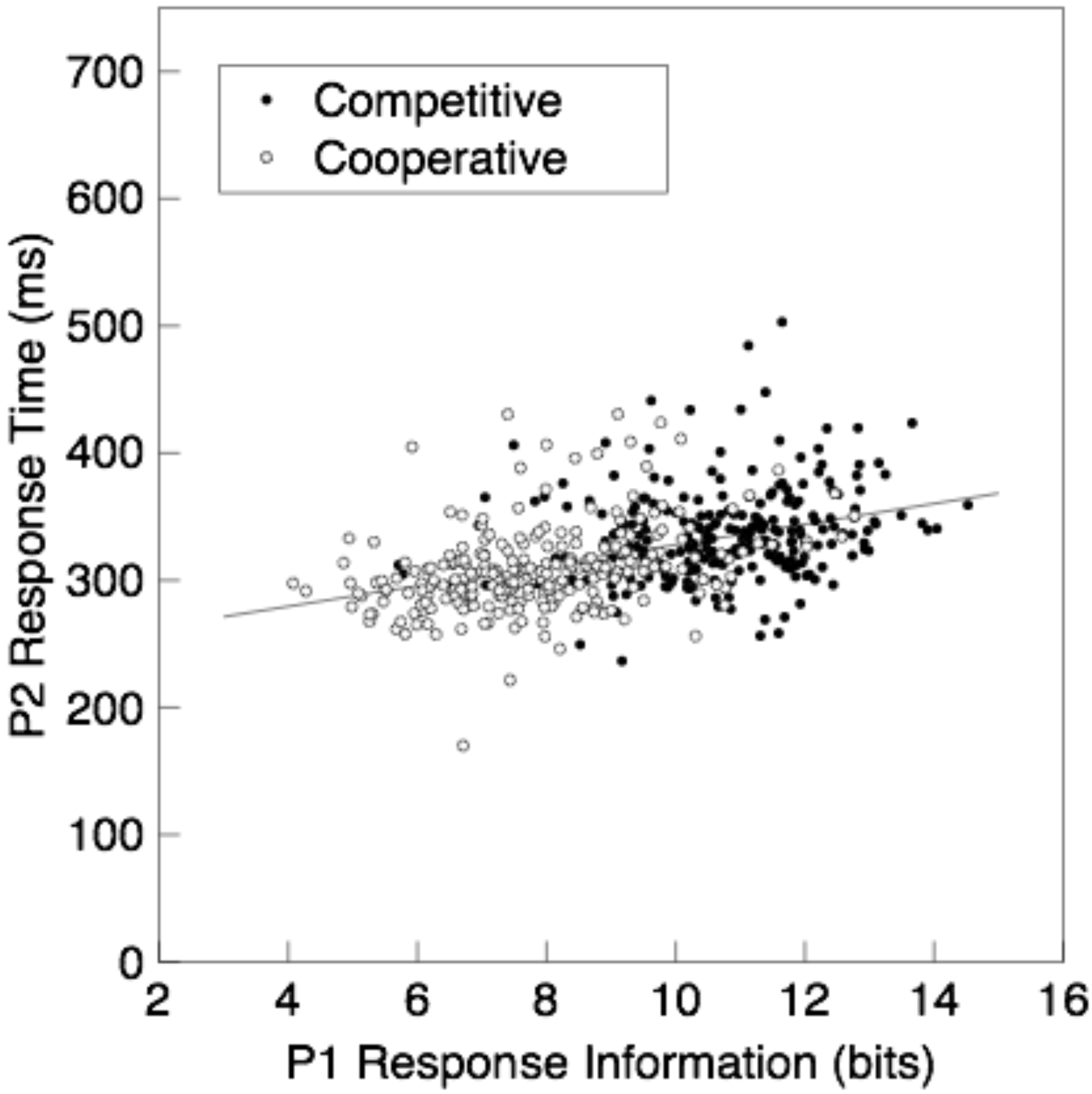

Figure 3. Median response time (after removing the random effects of subject) as a function of the information in response signal foreperiod, calculated from an empirical estimate of the foreperiod hazard function. The linear function represents the parameter estimates (i.e., the intercept and slope of the information effect) from the model fit.

In order to compare the results of Experiment 2 to those of Experiment 1, we also performed model fits on the combined data set. A model that included the effect of experiment (R^2 = .453) was substantially better than the null model, λ_{adj} > 1000, providing evidence that the responses in Experiment 2 were slower. As expected, a model that also included the effect of informativeness (R^2 = .495) was substantially better still, λ_{adj} > 1000. There was no evidence that a model in which the effect of informativeness varied across experiment (R^2 = .496) was any better, λ_{adj} = 0.49. In this aggregate analysis, there was only weak overall evidence for an effect of condition: A model with this additional effect (R^2 = .496) was only slightly better, λ_{adj} = 2.70.

Discussion

The results of Experiment 2 clearly show that the effect of information cannot be attributed to the use of nonverbal cues by P1 (as P1 had been replaced by a schematic finger), or to the mere presence of another actor. Thus, they lend support to our argument that it is predictability of the first response over time that determines the speed of the second response. Generally, response time was slower in Experiment 2 than in Experiment 1. It seems likely that the lack of a social context in Experiment 2 may have resulted in this difference (Aiello & Bouthitt, 2001; Zajonc, 1965). Another contributing factor may have been the differing nature of the initiating stimulus: The animation of a finger pressing a button may be less salient than a real finger making an actual movement.

Unlike Experiment 1, though, the information metric did not capture all of the variance due to condition. We suggest that this is due to differences in the expected distribution of responses. In the design used, there were relatively few trials in each block, so that participants had relatively little opportunity to familiarize themselves with the actual distribution of foreperiods. Instead, the uncertainty about when the response signal might occur is likely to have been strongly influenced by *a priori* expectations. Klemmer (1957) makes a similar argument and provides evidence regarding those *a priori* expectations. In contrast, participants in Experiment 1 were likely to have been much better able to generate reasonable expectancies about the distribution of responses by imagining (or remembering) how they might perform the P1 task. In Experiment 2, however, participants only ever experienced the P2 task and could not attribute the distribution of foreperiods to a peer. This meant that they had less ability to generate expectancies. Again, it is also possible that the differences in social context may have contributed to this difference in results.

General Discussion

The results of Experiment 1 showed clearly that opposing strategies of predictability and unpredictability were employed in cooperative and competitive versions, respectively, of an otherwise identical joint action. When the aim was to cooperate by facilitating their partner's performance, P1 aimed to be as consistent in the timing of their button presses as possible. Conversely, when the aim was to compete, P1 was much less predictable. The consequence of these different approaches to cooperation and competition by P1 was that P2 had faster response times in the cooperation version of the task than in the competition version, and this was true regardless of whether P1 was a person or a computer.

This change in P1's behavior in Experiment 1 was precisely indexed by an information measure derived from an empirical estimate of the hazard function. This information index can be described as the reduction in uncertainty of a response at any given point in the distribution of P1 responses. This index explained numerous effects observed in both experiments: 1) the differences across conditions in P1's pattern of response times; 2) differences across condition in P2's responses; 3) variations across subjects in how effective P1's strategy was; and 4) variations from trial to trial in P2's response times to particular P1 response times. Although related to aggregate statistics such as the standard deviation and mean of the P1 responses, our information index subsumed these variables and explained additional, unique variance. This supports a simple conceptual analysis of each participant's behavior: For P1, alterations in his or her pattern of response times were used to either minimize or maximize the information provided to P2 depending on whether the goal was cooperation or competition, respectively. For P2, his or her responses were rapid when the signal from P1 conveyed relatively little information, and slower when the signal from P1 conveyed more information. In this sense, the results of both experiments are congruent with classic evidence that response time increases with information (e.g., Hick, 1952; Hyman, 1953).

These results support earlier studies arguing for a role of predictability in cooperative joint action (Glowinski et al., 2013; Konvalinka et al., 2010; Sebanz & Knoblich, 2009; Vesper et al., 2011, 2013; Yin et al., 2016) and extend these findings to show the distinctly opposite pattern of behavior, namely unpredictability, in competitive joint action. By varying only the goals of the game and not the number of actors or the actions themselves in Experiment 1, we were able to provide strong evidence for diametrically opposing strategies in the very same action depending on the goals of the actors. By replacing P1 with a schematic finger in Experiment 2, we were able to confirm that these opposing strategies were effective based on their timing characteristics alone, and not as a result of subtle nonverbal cues or the mere presence of another actor.

Although Experiment 2 did show an effect of condition not evident in Experiment 1, it seems likely that this may have been a result of other differences between the two experiments, such as the lack of any experience at the P1 role for actors in Experiment 2, and the absence of any social context. One or both of these factors may have made it difficult participants in Experiment 2 to generate predictions regarding the likely distribution of (yoked) P1 response times. Perhaps informing participants ahead of time that the response times of the schematic finger in Experiment 2 were yoked to response times taken from actual participants performing under the same conditions might have given results more nearly identical to those of Experiment 1. Nevertheless, the main results as outlined above stand for P2's in both Experiments 1 and 2: P2's response times were highly dependent on the information provided by P1.

Although the present study had the strength of using a simple task that varied only in terms of the goals of the actors, we did not yet explore the impact of other cues on predicting the behavior of another actor in a joint action context. Here, actors were only able to vary the timing of their actions and no other kinematic features. In previous work, it has been shown that sensory inputs regarding a partner's kinematics can play a key role in helping to predict their actions (Streuber, Knoblich, Sebanz, Bulthoff, & de la Rosa, 2011), and that the ability to interpret these kinematic cues can vary according to expertise (Sebanz & Shiffrar, 2009). Future elaboration of our design might reveal more about how these other cues are used in cooperative versus competitive actions.

Whereas predictability in cooperation is clearly a beneficial strategy as it allows co-actors to time their actions appropriately, being unpredictable during competition is equally important. Often, we find ourselves competing with conspecifics for resources, mates, and other desirables, and in these cases being predictable would make us exploitable (Fundenberg & Tirole, 1991) and would thus be maladaptive. As such, identifying a social situation as cooperative or competitive, and then applying the appropriate strategy of being predictable or unpredictable, is likely a very important skill set in optimizing social behavior.

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