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Research paper

Team work under time constraints[☆]

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ABSTRACT

The existing literature has documented the advantages of teams as decision-making units across a wide array of environments. In this study, we explore the potential limits of such benefits. Specifically, we demonstrate that certain conditions, such as time constraints, can compromise team effectiveness, causing them to perform equally or even less effectively than individuals. Our findings indicate that under low time pressure, teams excel in coordination, achieving significantly higher efficiency compared to individuals. This result stems from teams' higher efforts and lower miscoordination. However, under high time pressure, teams lose their coordination advantages and struggle to reach an agreement, performing on par with individuals. We investigate the underlying mechanisms driving the detrimental effect of time pressure on performance by analyzing communication content and estimating the experience-weighted attraction learning model. Taking the evidence together, we conclude that teams' superior performance in coordination settings without time constraints can be attributed to open chat discussions, which create a shared understanding of the game.

1. Introduction

Teamwork is a prevalent aspect of decision-making in various contexts. Onuchic and Ray (2023) bring to light that in economics, co-authored papers make up over 70% of all published research. Taking a different perspective, Kim et al. (2022) argue that for most applications of game theory, each individual in a game has often been a team of players even if modeled as an individual decision maker (examples include spectrum auctions, R&D races, political parties, among others). Recognizing the ubiquity of team decision-making, a large strand of literature has investigated team decision-making compared to individual decision-making. Both theoretical and experimental literature have emphasized the benefits of team decision-making as it allows workers to combine their skills and knowledge (for the review of the literature, see Charness and Sutter, 2012 and Kugler et al., 2012).[1] In this paper, however, we experimentally examine the possible limits of such benefits, by investigating whether the superior performance of teams persists under time constraints in a coordination setting.

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[1] Onuchic and Ray (2023) theoretically explore the tension that could arise in teamwork due to the loss of an individual's ability to reveal personal ability and build reputation.

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Successful coordination is paramount in various organizational contexts, as coordination failures can lead to inefficiencies (Schelling, 1960; Arrow, 1974). Coordination frequently occurs under time pressures, such as client-imposed deadlines, emergencies, or natural disasters, highlighting the importance of examining the influence of time constraints. While existing research has demonstrated that teams can enhance coordination without time pressure (Feri et al., 2010; Chaudhuri et al., 2015; Sitzia and Zheng, 2019), the persistence of this advantage under time constraints has been overlooked.

Do teams under high time pressure still maintain higher efficiency than individuals? Identifying the causal impact of time pressure on coordination using observational data presents significant challenges, as time pressure and degree of coordination efficiency can reversely determine each other or/and be jointly influenced by other unobserved factors. To address these challenges, our study adopts an experimental methodology: we employ a 2×2 factorial design, varying the time allotted for decision-making (high vs. low time pressure) and the type of decision unit (individual vs. team).

The implications of time pressure on the performance gap between teams and individuals are not immediately evident. This uncertainty arises from the fact that the mechanism behind teams' superior performance remains unresolved. As a result, how time pressure influences the performance gap depends on the mechanism driving teams' advantage. We consider two possibilities.

On one hand, the cause of the performance gap could be that teams are more risk-loving than individuals. As a result, they could be less sensitive to strategic uncertainty, which is argued to be the main culprit of coordination failure. Since time pressure affects both teams and individuals, the performance gap should persist if teams' greater risk tolerance makes them less sensitive to strategic uncertainty, causing the gap to *persist* even under time pressure.

Alternatively, the performance gap may arise because intra-team discussions improve players' understanding of the game and their confidence in others' comprehension. High time pressure might hinder intra-team discussions, thus limiting opportunities for reaching agreement, teaching, and learning. If team discussions drive coordination success, then restricting discussion time through time pressure should *reduce* the performance gap or make it disappear. Therefore, understanding the impact of time pressure on coordination will also shed light on the potential driving forces that contribute to higher coordination among teams compared to individuals in coordination games conducted without time constraints.

Our results show that under low time pressure, teams acting as decision units are significantly better at coordination than individuals. Specifically, under low time pressure, teams achieve 69% efficiency, while individuals under low time pressure reach 53% efficiency. Two underlying factors are found to drive teams' superior performance under low time pressure. First, teams choose considerably higher efforts than individuals. Second, teams reach a lower degree of miscoordination than individuals.

Examining teams and individuals under high time pressure, we observe that time pressure wipes off the efficiency gains of teams relative to individuals. Teams under high time pressure only reach 56% efficiency, which is not statistically distinct from the 49% efficiency reached by individuals under such pressure. This suggests that teams' better performance in coordination settings is contingent upon having sufficient time for making decisions. Further investigation into the factors behind this diminished performance reveals that it is not primarily attributed to a lack of teams' ambition to choose higher effort under time pressure. Instead, the key factor undermining team performance is identified as the increased likelihood of divergent effort choices among teams and the decreased likelihood of reaching consensus within teams.

To further understand why time pressure disrupts the efficiency gains of teams, we examine the communication content during team decision-making. Our evidence suggests that sufficient teaching and learning discussions might lead to efficiency gains. To better understand the underlying mechanisms, we employ the experience-weighted attraction (EWA) learning model of Camerer and Ho (1999). The model estimation reinforces key findings. Under low time pressure, teams are more attracted to payoff-dominant choices than individuals, which implies a higher probability of playing more profitable strategies. Consequently, teams reach equilibrium faster and exhibit better levels of efficiency. However, this advantage dissipates under high time pressure.

2. Literature review

This study contributes to three distinct strands of literature. First, it builds upon the extensive experimental economics research focusing on team decision-making in scenarios characterized by low time pressure (see Charness and Sutter, 2012 and Kugler et al., 2012 for reviews). While a comprehensive review of this vast literature is beyond the scope of our study, we highlight some key findings. Compared with individuals, teams tend to align more closely with game-theoretic predictions in various settings featuring unique Nash equilibria, such as dictator games, public goods games, and other settings (Cason and Mui, 1997; Bornstein et al., 2002; Cooper and Kagel, 2005; Kugler et al., 2007; Luhan et al., 2009; Müller and Tan, 2013; Balafoutas et al., 2014; Cason and Mui, 2019; Nielsen et al., 2019; Miller and Rholes, 2023). This alignment suggests that teams exhibit a higher degree of cognitive sophistication. Moreover, when decisions involve multiple Pareto-ranked Nash equilibria, teams typically coordinate more effectively by converging to a more efficient equilibrium (Feri et al., 2010; Chaudhuri et al., 2015; Sitzia and Zheng, 2019). In many real-world markets and organizations, decision-making is inherently constrained by time. This challenge is particularly pronounced for teams due to intrinsic communication delays and other process-related constraints. We extend the existing literature by examining both team and individual decision-making under varying levels of time pressure.

Our paper is also related to the literature on time pressure. The literature focuses on how time constraints influence individuals' preferences and choices (for an overview, see Spiliopoulos and Andreas, 2018). For example, individuals tend to be more risk-seeking under higher time pressure (e.g., Kocher et al., 2013; Saqib and Chan, 2015).[2] More related to our work,

[2] Some studies have reasoned that cooperation is a more intuitive choice by showing that subjects who choose quickly (have lower response time) are more likely to choose cooperative action than others who take longer to come to a decision (see Piovesan and Wengström 2009, Rand et al. 2012). However, follow-up papers put significant doubt on the "social heuristic hypothesis" that people are intuitively cooperative, see, for example, Tinghög et al. (2013) and Alós-Ferrer and Garagnani (2020).

Belloc et al. (2019) and Poulsen and Sonntag (2020) find that high time pressure increases individual coordination levels in a coordination game. Our study extends the literature on time pressure from individual decision-making to a team decision-making environment, a commonplace for many settings in real life, in which more interaction and thus time for decisions are expected to be needed.

Finally, this paper is related to the literature on institutions that promote coordination, as we emphasize the limitations of teams as an institution to resolve coordination failures. Studies have examined ways to aid successful coordination via various institutions, such as costly and costless communication (Van Huyck et al., 1993; Cooper et al., 1992; Charness, 2000; Blume and Ortmann, 2007; Brandts et al., 2015), commitment (Avoyan and Ramos, 2023), between-group competitions (Bornstein et al., 2002; Riechmann and Joachim, 2008), endogenous and fixed neighborhood or group formation (Riedl et al., 2016; Yang et al., 2017; Caparrós et al., 2020), voluntary reward (Yang et al., 2018), gradual group size growth (Weber, 2006), social identities (Chen and Chen, 2011; Chen et al., 2014), transfer of learning across games (Devetag, 2005; Cason et al., 2012), and teams as decision units (Feri et al., 2010; Chaudhuri et al., 2015). In addition, research has also shown that reducing the cost of effort (Van Huyck et al., 1990; Goeree and Holt, 2005) and increasing the benefits of coordination (Brandts and Cooper, 2006) both promote successful coordination. Further studies have explored the effects of placing an additional payment on the payoff-dominant outcome, either as a one-time increase in stakes (Hamman et al., 2007) or a gradual increase in stakes (Ye et al., 2020). Building on this body of work, our study focuses on how time constraints affect coordination when teams serve as the decision-making units.

3. Experimental design

In this section, we outline the experimental setup, including the description of the game, the treatment conditions, the choices of parameters, as well as the details on implementation.

3.1. The game

The game we study is a weak-link game (also referred to as a minimum-effort game).[3] The game is a stylized version of settings where production or a group outcome depends on the laggard of the group. Examples include factory line work, scheduling, and efforts for containment of contagious diseases. On a factory line, the productivity of the entire assembly depends on the slowest stage of the process, as each individual's task completion is a prerequisite for the next step. In scheduling contexts, the timely completion of a group project is compromised by the participant who finishes last. Similarly, when containing a contagious disease, the effectiveness of efforts to halt the spread is limited by the least vigilant individual, since one person's lapse can undermine the collective containment strategy. Drawing on these types of scenarios, we now turn to the stylized version of these settings and the experimental framework.

Participants engage in a weak-link game characterized by the following components: $(I, (E)_{i\in I}, (\pi_i)_{i\in I})$, where $I = \{1, 2, \dots, 5\}$ is a set of decision units[4]; $E = \{1, 2, \dots, 7\}$ is a finite set of effort levels available to each unit i; and $\pi_i(\mathbf{e})$ is the payoff for each unit i given the strategy profile $\mathbf{e} \in \mathbf{E}$, where $\mathbf{e} = (e_i)_{i\in I}$ and $\mathbf{E} = \prod_{i\in I} E$. The payoff function is given by

$$\pi_i(\mathbf{e}) = a + b \cdot \min_{j\in I} e_j - c \cdot e_i, \tag{1}$$

where a, b, and c are real, nonnegative constants. In particular, the parameters used in the experiment are $a = 60$, $b = 20$, and $c = 10$. Note that the minimum of the group includes i's own choice and the payoff decreases with a higher choice of effort and increases with the minimum effort provided within a group. Let $\bar{e}$ ($\underline{e}$) be the highest (lowest) element of E and let $\bar{\mathbf{e}}$ ($\underline{\mathbf{e}}$) be the profile for which all units choose $\bar{e}$ ($\underline{e}$).

The game described above has multiple equilibria.[5] In particular, every decision unit picking the same effort level is an equilibrium. All these equilibria are ranked, from the payoff-worst in which all decision units choose $\underline{e}$ to payoff-best (payoff-dominant) in which all decision units choose $\bar{e}$ (Harsanyi and Selten, 1988). Beginning with Van Huyck et al. (1990), numerous studies have shown that subjects do not achieve payoff-dominant equilibrium.[6]

Following the convention in literature, we describe the payoffs to subjects in a matrix form (see Table 1). For the team-based treatments, the payoffs in the matrix are told to be a *per participant payoff* for each team member. That is, for instance, if a team

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3 Both terms, "weak-link game" and "minimum-effort game", are widely and interchangeably used in the literature. The concept of weakest-link production, where the output of a public good is determined by the minimum contribution, was brought to light by Harrison and Hirshleifer (1989). As noted by Cooper and Weber (2020), a coordination game with a similar payoff structure was later referred to as the "minimum-effort game" in Van Huyck et al. (1990) and as the "weak-link game" in Knez and Camerer (1994).

4 In the main text of the paper, we define a group as consisting of 5 decision units, with each decision unit composed of 3 participants (15 participants total per group) in team-based treatments and of 1 participant (5 participants total per group) in individual-based treatments, respectively. However, in the instructions, we use different terminology: What the main text calls a group of 15 participants is referred to as a unit, and what the main text calls a unit of 3 participants is referred to as a team.

5 In our experiment, the number of decision units in a game can be reduced to less than 5 if any teams fail to reach an agreement or decision units fail to submit decisions within the time constraint. Given such possibilities, each player choosing not to submit a choice (choosing $\emptyset$) is also an equilibrium, that is, the set of actions is $E \cup \{\emptyset\}$ and $\pi_i(\emptyset, e_{-i}) = 0$. We provide further information and discussion in Section 3.2.

6 There are a few cases in which subjects exert higher effort though. For example, Engelmann and Normann (2010) find that the higher the share of Danish subjects in a group, the higher the minimum effort levels. In Van Huyck et al. (1990), groups comprising of only two subjects with access to the history of play from the previous period achieve high coordination rates.

Table 1
Payoffs in the weak-link game.

Own number	Smallest number chosen in the group						
	7	6	5	4	3	2	1
7	130	110	90	70	50	30	10
6		120	100	80	60	40	20
5			110	90	70	50	30
4				100	80	60	40
3					90	70	50
2						80	60
1							70

Table 2
Summary of experimental design.

Treatment	*Time Pressure*	*Teams*	*# Groups*	*# Subjects*
Individual LTP (*I-LTP*)	Low	No	6	30
Individual HTP (*I-HTP*)	High	No	6	30
Team LTP (*T-LTP*)	Low	Yes	6	90
Team HTP (*T-HTP*)	High	Yes	6	90

chooses seven and the minimum effort in its group is 7, every member of the team will receive 130 points in that period, rather than splitting that 130 points by 3 team members. This approach keeps the individual marginal incentives constant throughout the individual and team treatments.[7]

3.2. Treatments

We use four distinct treatments in our study, which we describe one at a time, starting with the individual treatments, followed by the team treatments.

Individual treatments Five subjects play the weak-link game for 20 periods. In each period, each subject is asked to choose a number from the feasible set, i.e., 1 to 7, independently. Each subject is informed about the smallest number in their group after each period. Subjects get paid according to Eq. (1) based on their own number and the smallest number (as effort chosen) in their group.

In Individual Low-Time-Pressure treatment (*I-LTP*, hereafter), subjects are given 3 min to make their decisions, while subjects in Individual High-Time-Pressure treatment (*I-HTP*, hereafter) are given 30 s to make their decisions.[8]

Team treatments A group of 15 participants is randomly divided into 5 teams with 3 members each. Team assignments remain the same throughout the session. These 5 teams play a weak-link game for 20 periods. In each period, each team member is asked to submit their choice of team number. A team reaches a joint team decision by unanimously agreeing on a single number to be chosen by all members. If different numbers are submitted, no agreement is reached and that team is excluded from participating in the group weak-link game. Team members who did not reach an agreement receive no payment for that period.[9] In such cases, the minimum number of a group is calculated based on the single number chosen by the remaining units that successfully reach an agreement.

The experimental instructions do not specify how team members should reach a team decision. Instead, team members are given access to an electronic, open, free-form chat, allowing each member to propose a choice for the team's decision individually on their computer screen (see Appendix Figure B1, for a sample screen).[10] Participants are free to communicate during the chat time but are asked to refrain from revealing their identities and using abusive language.

In the Team Low-Time-Pressure treatment (*T-LTP*, hereafter), subjects have access to the chat and decision screen for three minutes per period. In contrast, the Team High-Time-Pressure treatment (*T-HTP*, hereafter) limits access to 30 s.

Table 2 summarizes treatment conditions and the number of groups and subjects for each treatment.

[7] While the marginal incentives remain identical across individual and team environments, subjects may hold other-regarding preferences either exclusively for their teammates or more broadly for the entire group. Investigating how such social preferences influence coordination outcomes, by amplifying the disutility of miscoordination or increasing the appeal of higher-effort equilibria, may be a promising direction for future research.

[8] Exceeding the time limits results in a no-choice outcome. However, no subject in the individual treatments actually encountered this situation.

[9] This payment rule provides a strong incentive for team members to reach an agreement since it provides zero outside option. It also reflects the natural consequence of receiving no benefit in the absence of team agreement, as seen in many real-world settings.

[10] We follow Feri et al. (2010) in using an electronic chat to allow access to the chat logs for analysis. Alternatively, the communication can be implemented by restricting it to choices only or using face-to-face (FTF) communication. However, FTF communication poses greater implementation challenges, such as managing the precise start and end of discussions, transcribing communication content ex-post, and ensuring that all five teams are in separate rooms to avoid overhearing one another, among other issues.

3.3. Parameter choices

We chose to closely follow the parameters (e.g., number of periods, team and group sizes, payoffs structure and procedures), instructions, and protocol, as used in Feri et al. (2010), to ensure that we could replicate their findings that teams are better at coordination than individuals. Regarding modifications, while Feri et al. (2010) initially allotted subjects a two-minute time frame to reach an agreement, we extended this to three minutes to ensure time pressure was sufficiently low in I-LTP and T-LTP treatments.

The rationale behind choosing 30 s for T-HTP treatment is two-fold. The first is to create enough time pressure. The data from low-time-pressure treatments reveals that teams with low time pressure take an average of 54.22 s to submit their choices. The time constraint is even more severe for earlier periods, with teams spending 99.8 s in the first period and an average of 69.82 s in the first ten periods. By comparison, individuals with low time pressure take, on average, 3.4 s to decide and submit their choice in each period. Appendix Figure A1 (g) presents how time to make a decision evolves over 20 periods. The second objective of choosing 30 s instead of an even shorter time frame is to ensure teams still have time to make decisions based on meaningful communication so that team choices are not purely random forced ones under time pressure. Our results show that teams in T-HTP treatment still have a number of messages exchanged confirming that our choice of time frame while binding still allowed an exchange (see more details in Table 6).

3.4. Implementation

This experiment was conducted at Interdisciplinary Experimental Laboratory (IELab) at Indiana University (IU) during the Fall of 2021 and Spring of 2023, using software z-Tree (Fischbacher, 2007). Subjects were recruited from the general undergraduate population via ORSEE recruitment system (Greiner, 2015).[11] The instructions were read aloud, and the paper copies were distributed to all subjects. (Refer to Appendix C for instructions of the T-HTP treatment in the experiment.) The experiment lasted approximately 45 min, and subjects earned an average payoff of $17, which included an $8 show-up fee. In the experiment, the payoffs in the game were denominated in points. Each point was converted to US dollars at the rate of 200 points to $1.

4. Discussion of predictions

What are the potential effects of time pressure on the performance gap between teams and individuals in coordination games? The answer is ambiguous, primarily because the reasons behind teams' superior performance remain unclear. While it is well-documented that teams generally outperform individuals, the specific forces driving this advantage remain an open question. This section explores the possible mechanisms through which time pressure would affect the performance gap between teams and individuals by examining possible driving forces and their interaction with time constraints.

Beginning with the seminal work of Van Huyck et al. (1990), extensive experimental evidence has consistently shown that players tend to converge towards safer, albeit lower-payoff, equilibrium in coordination games.[12] Strategic uncertainty has been identified as the primary culprit of the coordination failures.

Since teams tend to be more risk-taking than individuals (Bougheas et al., 2013), this may explain their superior performance in coordination games. Teams might be less sensitive to strategic uncertainty, leading them to take on greater risks and achieve better coordination outcomes. But how might time pressure affect the performance gap if risk tolerance is the key mechanism?

Time pressure has been shown to increase risk-taking behavior in individuals (Kocher et al., 2013; Saqib and Chan, 2015). When faced with the same time pressure, individual team members within the team contexts are also likely to be affected in a similar way. If teams outperform individuals because they are more risk-tolerant, and time pressure increases risk-taking across the board, then the performance gap should persist, as both teams and individuals would experience a similar shift in behavior.

An alternative mechanism behind the performance gap could be intra-team communication. This interaction may facilitate superior performance by enabling team members to better understand the game and develop more effective strategies (Charness and Sutter, 2012). Even in the absence of open communication, the presence of "teachers" within teams has been shown to improve outcomes (Hyndman et al., 2012). If intra-team interactions and synergies drive the performance gap, how would time pressure affect such synergy?

Time pressure is likely to restrict some aspects of team discussion, potentially limiting team members' ability to consider the payoff structure and collaboratively explore potential strategies. Consequently, this disruption could hinder team performance, narrowing the gap between teams and individuals.

The discussion above outlines how time pressure might influence the superior performance of teams in coordination games. The empirical findings presented in the next section offer insights into not only the overall effects of time pressure but also the underlying mechanisms that contribute to teams' superior performance. The discussion above highlights two possible outcomes, driven by distinct mechanisms: *risk tolerance* and *team interaction*.

The possible mechanisms are summarized in Fig. 1.

[11] Appendix Table A3 shows that 11 out of 12 comparisons of demographic characteristics support successful randomization (The only exception is that subjects in I-HTP treatment have higher GPA than subjects in I-LTP treatment).

[12] The equilibrium selection problem arising from the multiplicity of equilibria in coordination games is a challenging problem and the prevalent selection criteria introduced in Harsanyi and Selten (1988) are the payoff- and risk-dominance. See, also, Carlsson and Van Damme (1993) where perturbation in payoffs leads the players to conform to risk-dominant equilibrium in a 2×2 coordination game. For selection based on the salience of own payoffs, refer to Leland and Schneider (2015, 2018).

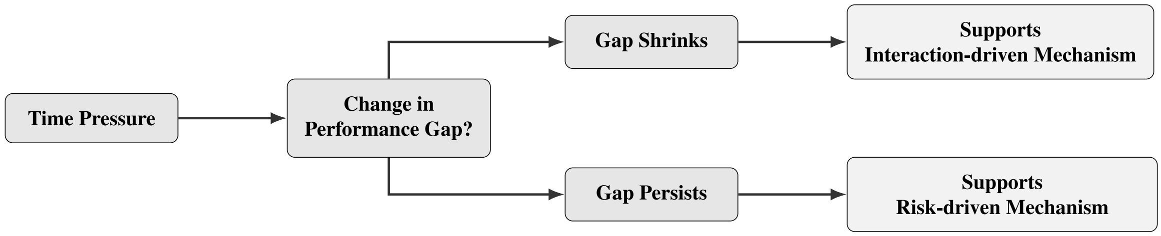

Fig. 1. Possible effects on performance gap and mechanisms.

Table 3
Efficiency levels.

	Team	*Individual*	Comparison
	[1]	[2]	[1] vs. [2]
LTP	69.23	53.46	***
	(3.72)	(2.48)	
	[3]	[4]	[3] vs. [4]
HTP	55.67	48.71	#
	(4.10)	(0.60)	
Comparison	[1] vs. [3]	[2] vs. [4]	[2] - [1] vs. [4] - [3]
	***	#	*

Note: (1) Each observation is determined by the average efficiency level of an individual or team over 20 periods, since the efficiency level is an outcome defined at these respective levels. Each treatment comprises 30 observations. (2) Standard errors are presented in parentheses. (3) # indicates non-significance at conventional statistical levels, while *,** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

5. Results

This section presents our primary findings, starting with comparisons across treatments using aggregate measures, followed by an analysis of various variables commonly examined in the literature. Next, we present findings from examining intra-team communication to understand the potential mechanisms contributing to performance differences. Lastly, we estimate the experience-weighted attraction learning model to further investigate underlying mechanisms driving the main effects.

5.1. Main results

We begin by focusing on a key measure of efficiency outcome—the normalized efficiency. It is defined as $Normalized Efficiency = \frac{Actual-Min}{Max-Min} \times 100\%$, where $Actual$ is the average amount earned in a treatment, and Min (Max) is the minimum (maximum) possible amount that a subject can earn. The normalized efficiency measure captures the efficacy of different treatments relative to the best possible outcomes.[13] In Table 3, we present normalized efficiency across the four treatments examined in this study.[14]

The normalized efficiency reaches 69.23% in T-LTP treatment, significantly surpassing the 53.46% observed in I-LTP treatment (Mann–Whitney two-sided tests, $p < 0.01$).[15,16] Such a high level of efficiency in T-LTP is comparable to that of cross decision-making units communication treatments in the literature. For instance, in Blume and Ortmann (2007) and Deck and Nikiforakis (2012), pre-play cheap-talk interaction improves coordination and boosts normalized efficiency to 69% and 71% from 34% and 44%, respectively. These findings reaffirm the consensus in the existing literature regarding the superior coordination abilities of teams compared to individuals in coordination games.

A closer examination of Table 3 reveals a curious pattern. Achieving high efficiency in the T-LTP treatment appears to depend on the absence of significant time pressure.. When we introduce time pressure to teams, we observe a substantial decline in efficiency,

[13] In essence, efficiency measures are linear transformations of payoff outcomes. However, the former outperforms the latter in a sense that it is adjusted for specific experimental payoff parameters, which facilitates comparisons with results from previous studies. For example, in groups of six participants, Deck and Nikiforakis (2012) and Avoyan and Ramos (2023) report baseline treatment results of 44% and 48% normalized efficiency, respectively. For this reason, we focus on efficiency rather than payoff measures as the main outcomes. Appendix Table A4 provides results based on payoff measures, which are qualitatively identical to the results based on efficiency measures.

[14] For ease of comparisons across treatments, we focus on aggregate statistics and the overall treatment effects in this section, and we provide more details on variables of interest over the 20 periods in Appendix Figure A1.

[15] For normalized efficiency and other variables discussed later, such as effort, miscoordination, frequency of agreement, and decision time, the individual or team average across 20 periods constitutes a single observation, given the definition of these variables at individual or team level, with $n = 30$ for each treatment. In contrast, for minimum effort and effort deviation, the group average across 20 periods is considered as one observation, with $n = 6$ for each treatment.

[16] Throughout this section, Mann–Whitney two-sided tests are used for comparisons across different treatments unless otherwise specified.

Table 4
Summary statistics.

	T-LTP		T-HTP		I-LTP		I-HTP	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Panel 1. Effort								
(a) Effort	4.309	0.415	4.518	0.393	2.600	0.244	2.335	0.089
(b) Minimum Effort	3.892	1.054	3.712	0.974	1.775	0.646	1.333	0.095
Panel 2. Coordination								
(c) Miscoordination	0.433	0.063	0.904	0.185	0.825	0.099	1.002	0.074
(d) Effort Deviation	0.356	0.106	0.807	0.276	0.927	0.141	1.046	0.064
Panel 3. Agreement								
(e) Frequency of Agreement	0.978	0.005	0.827	0.029	1.000	0.000	1.000	0.000
(f) Decision Time (second)	63.688	6.905	18.267	0.814	6.315	4.979	3.548	0.515

Note: (1) "Effort" refers to the chosen effort by teams or individuals. "Minimum Effort" denotes the lowest effort within a group of five teams or individuals. "Miscoordination" is defined as the absolute difference between a decision maker's effort and the group minimum of all units, while "Effort Deviation" represents the standard deviation of efforts within the group. (2) For variables such as effort, miscoordination, frequency of agreement, and decision time, the individual or team average across 20 periods constitutes a single observation, given the definition of efficiency level at these respective tiers, with $n = 30$ for each treatment. In contrast, for minimum effort and effort deviation, the group average across 20 periods is considered one observation, with $n = 6$ for each treatment.

dropping to levels of individual treatment. Specifically, normalized efficiency decreases from 69.23% in T-LTP to 55.67% in T-HTP ($p < 0.01$) when teams face high time pressure. These findings demonstrate that teams outperform individuals in terms of efficiency, but only when they operate without binding time constraints, suggesting that when evaluating a policy involving teams one needs to take into account the possible presence of time constraints and their consequences.

Does time pressure have the same effect on individuals? Table 3 shows that the efficiency level of 53.46% in the I-LTP treatment is statistically indistinguishable from that of 48.71% in the I-HTP treatment, revealing time pressure at the level of our study does not significantly influence the efficiency levels in individual treatments. Our findings indicate that the effect of time pressure on decision-making processes varies significantly depending on whether individuals are operating independently or within a team context.

Overall, we find that the efficiency levels of teams with high time pressure, individuals with high and low time pressure are all statistically indistinguishable from each other. It is worth noting that our intention is not to suggest that time pressure has no impact on individual decision-making. Rather, our results highlight that a given level of time pressure can produce differential effects when applied to individuals versus teams. In Appendix Table A5 and Table A6, we further consider two alternative efficiency measures to account for the importance of team disagreements on the entire group's performance, and report a detailed discussion of the alternative measures and highlight how teams under high time pressure may perform worse than individuals.

Next, we turn to the mechanisms underlying the results presented above.

Mechanisms underlying the main results The observed reduction in efficiency across treatments can be attributed to three distinct mechanisms. Recall the payoff function in the weak-link game, as described in Eq. (1). Efficiency loss can arise from three primary sources. First, subjects choose efforts lower than the payoff dominant effort level. Second, subjects miscoordinate and select different efforts that lead to a wasted cost of choosing higher effort levels. Third, teams fail to reach an agreement. To identify the primary driver of the observed efficiency differences across treatments, we examine various measures corresponding to each of these effects.

Our findings reveal that the disparity is not driven by a lack of 'ambition' to exert effort in the T-HTP treatment. In both T-LTP and T-HTP, most team members try to achieve higher overall efforts, as reflected by comparable average and minimum effort levels in both treatments, see Table 4, panel (1). Thus, irrespective of whether time pressure is low or high, teams consistently exhibit higher effort levels than individuals.

Teams under low time pressure exhibit significantly less miscoordination, as shown in panel (2) of Table 4. Miscoordination—measured as the difference between the five chosen efforts and the actual minimum effort in each group—in T-LTP is only half of that in I-LTP and the difference is statistically significant ($p < 0.01$). Similarly, when we examine the average standard deviation of effort decisions within the group for a given period, teams in T-LTP exhibit less than half of the deviation observed in I-LTP ($p = 0.01$).

In contrast, imposing high time pressure reduces coordination levels in teams for both measures ($p = 0.081$ for miscoordination and $p = 0.127$ for effort deviation), while its impact on individual treatments is minimal ($p > 0.1$ for both measures). Consequently, under high time pressure, the difference in coordination levels between teams and individuals becomes negligible ($p > 0.1$ for both measures).

Recall how a team reaches an agreement. Team members communicate through an open chat and can earn a non-zero payoff if they agree on the same effort decision, allowing them to participate in group coordination. In panel (3) of Table 4, we present the frequency of agreement, highlighting how often teams can reach agreements in T-LTP and T-HTP, respectively. Under high time pressure, teams exhibit a significantly higher proportion of failed agreements ($p < 0.01$), which further explains their diminished

Table 5
Regression results.

Dependent variables	Efficiency	Frequency of Agreement	Decision time (second)	Effort	Minimum Effort	Mis-coordination	Effort Deviation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I-HTP	−0.048	−0.000	−2.767	−0.265	−0.442	0.177	0.119
	(0.054)	(0.000)	(1.958)	(0.534)	(0.612)	(0.148)	(0.145)
T-LTP	0.178*	−0.022***	57.373***	1.742*	2.117*	−0.368**	−0.571***
	(0.099)	(0.007)	(13.208)	(1.058)	(1.159)	(0.183)	(0.166)
T-HTP	0.022	−0.173***	11.952***	2.094**	1.968*	0.185	−0.091
	(0.094)	(0.028)	(2.346)	(0.960)	(1.095)	(0.291)	(0.288)
Period	0.029***	0.025***	−1.864**	−0.426***	−0.144**	−0.304***	−0.115***
	(0.009)	(0.009)	(0.865)	(0.059)	(0.062)	(0.048)	(0.044)
Period^2	−0.001**	−0.001***	0.048*	0.013***	0.005**	0.010***	0.003
	(0.000)	(0.000)	(0.028)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.368***	0.862***	19.067***	5.134***	2.623***	2.629***	1.768***
	(0.071)	(0.044)	(5.502)	(0.532)	(0.660)	(0.287)	(0.225)
Observations	2400	2400	2400	2283	475	2283	475
R^2	0.1565	0.1592	0.4228	0.2840	0.2673	0.1794	0.2366
Estimated differences							
(T-LTP)-(T-HTP)	0.156	0.152***	45.422***	−0.359	0.148	−0.554**	−0.480*
	(0.113)	(0.028)	(13.164)	(1.229)	(1.347)	(0.275)	(0.273)
(I-HTP) - (T-HTP)	−0.067	0.173***	−14.718***	−2.360***	−2.410**	−0.008	0.209
	(0.077)	(0.028)	(1.638)	(0.809)	(0.916)	(0.256)	(0.262)
[(T-LTP) - (T-HTP)] - [(I-LTP) - (I-HTP)]	0.116	0.152***	42.655***	−0.532	−0.206	−0.377	−0.362
	[0.126]	[0.028]	[13.309]	[1.338]	[1.479]	[0.313]	[0.309]

Note: (1) Results reported in the table are derived from random effect linear regressions. Standard errors, clustered at the group level, are presented in parentheses. The reference group is I-LTP. (2) "Effort" represents chosen effort by each team or individual. "Minimum Effort" represents the minimum effort within a group. "Miscoordination" is defined as the absolute difference between a decision maker's chosen effort and the minimum effort within the same period. "Effort Deviation" is the standard deviation of efforts in the group. (3) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

performance. Time pressure impedes teams' ability to reach a consensus, leading to their exclusion from group coordination and resulting in losses.

Panel (3) of Table 4 shows that imposing high time pressure significantly reduces decision time for teams ($p < 0.01$) but not for individuals ($p = 0.289$). Although decision time may not necessarily directly influence efficiency levels, it reflects the extent to which our experimental manipulation of time pressure affects individual and team decision-making heterogeneously. That is, time pressure seems binding for teams but not for individuals, which results from the fact that team decision-making is more time-demanding compared to that of individuals.

Finally, we conduct a random-effect regression analysis, incorporating all previously mentioned measures as endogenous variables.[17] Standard errors are clustered at the group level, treating each group as an independent observation.

The regression results, as presented in Table 5, are qualitatively in line with results from the aforementioned non-parametric tests. They reinforce key trends, such as the importance of group-level variables (effort deviation and minimum effort), and show higher statistical significance in the regression framework. Nevertheless, some individual- or team-level variables (efficiency, frequency of agreement, decision time, effort, and miscoordination) exhibit less pronounced distinctions.[18]

Next, we move to investigate the chat content to understand the differences leading to high levels of miscoordination and disagreement in T-HTP compared to T-LTP.

5.2. Chat content analysis

To identify possible differences in communication within teams arising from time constraints, we categorize the chat content in T-LTP and T-HTP treatments. For this purpose, two research assistants (RA) were tasked to classify all messages into four predefined categories.[19] Our analysis focuses on the four distinct categories, each corresponding to a specific hypothesis concerning the mechanisms influencing effective team decision-making.

[17] The use of the random-effect regression is due to the panel structure of the data. A Lagrange Multiplier test for random effect is executed to aid the decision between a random-effects regression and a straightforward OLS regression. For all regressions depicted in Table 5, the null hypothesis that there is no significant difference across units, i.e., no panel effect, is rejected.

[18] One might be concerned that the initial learning periods influence our findings disproportionately. However, the significance level of our results remains largely consistent, even upon the exclusion of the first one, two, or five periods (see Appendix Table A7, Table A8, and Table A9).

[19] The RAs were undergraduate and graduate students in the economics department at Indiana University who were unaware of the purpose of our study. The categories, outlined in Table 6, had been ex-ante determined by the research team and provided to the RAs.

Table 6
Content analysis of chat messages.

Summary statistics for each message category	Average no.		Frequency	
	T-LTP	*T-HTP*	*T-LTP*	*T-HTP*
C_1: Questions or explanations about the environment or payoff structure; answers to the questions	64.200***	19.533	0.384*	0.278
C_2: State or counter a proposed plan (no engagement similar to Category 1)	8.980***	27.933	0.054***	0.418
C_3: Agreeing with the proposed team strategy and stating intention to follow the plan	33.130***	12.550	0.198	0.188
C_4: Inconsequential content (such as saying hi)	60.933*	8.903	0.364*	0.129

Note: (1) The columns headed "Average no." represent the average number of messages in each category in T-LTP and T-HTP treatments, while the columns headed "Frequency" denotes the fraction of messages in each category relative to all messages in the two treatments. (2) The statistical analysis employs OLS regression, with the dependent variable being the average number or frequency of messages in each category, and the independent variable is a dummy variable signifying the treatments. Standard errors are clustered at the group level. (2) * and *** indicate statistical significance at the 10% and 1% levels, respectively.

As discussed in Section 4, Hyndman et al. (2012) emphasize the significance of the presence of "teachers" in facilitating efficient play. Therefore, our first category captures messages related to teaching and learning about the game. The second category represents intentions of choice that lack instructional content, contrasting with the first category. These messages propose choices or counter-propose choices without providing explanation or clarification. The third category includes messages that contribute to establishing common knowledge of proposed effort choices — a crucial aspect in coordination games (see Chen et al. 2021). The last category contains inconsequential messages — those unrelated to the game, effort intentions, or strategies. These messages may indicate a level of group engagement in conversations beyond the game (see Chen and Chen 2011).[20]

Table 6 presents the results of our content analysis, including the average number and frequency of messages within each category for both T-LTP and T-HTP treatments. Time pressure leads to a shift in the composition of team communication content. Specifically, teams in the T-LTP treatment exhibit a higher prevalence of C_1 messages, while teams in the T-HTP treatment tend to produce more C_2 messages, both in terms of the absolute number and frequency. Under high time pressure, the task of reaching a consensus becomes inherently more challenging for team members. Indeed, there is limited time for team members to engage in extensive discussions about the game's structure and optimal responses to other teams' prior decisions. Furthermore, C_3 messages involving reassurance, which can help establish common knowledge of effort choices among team members, appear more under low time pressure than under high time pressure. Taking into account the overarching results on performance, it is reasonable to speculate that discussions involving learning and reassurance constitute crucial components contributing to better performance of teams over individuals under low time pressure.

We next examine the use of messages in each category over time. Fig. 2 illustrates the trends of the average number of messages across four categories over time in T-LTP and T-HTP treatments. One particularly striking observation is the stark contrast in the dynamics of using teaching and learning messages (C_1 category) between the two treatments as shown in Fig. 2(a). In the T-LTP treatment, C_1 messages are especially prevalent in the early periods. However, their frequency declines markedly over time, eventually approaching levels similar to those observed in the T-HTP treatment as the periods progress. This pattern aligns with an intuitive interpretation: teaching and learning messages are most common in the early stages of play but diminish as team members converge on stable decisions. A similar dynamic is observed for C_3 messages, though the decline is less pronounced than that for C_1 messages.

We note two limitations of the chat content analysis. First, it applies only to team treatments with an open chat feature. Second, despite the exogenous classification of the chat messages, concerns may remain about the objectivity of the categorization. To address these limitations, we further employ a structural estimation of a behavioral model, which is solely based on decisions over time. This approach allows us to account for decision-making in all four treatments and focus on calibrated parameters that provide key insights into the behavioral mechanisms underlying the aggregate results (see DellaVigna, 2018).

5.3. Experience-weighted attraction learning model

In this section, we aim to gain a further understanding of the dynamics of teams and individuals under various time pressures by employing the experience-weighted attraction (EWA) learning model. Developed by Camerer and Ho (1999), this model combines reinforcement and belief-based learning approaches.[21]

[20] Examples of messages from our data include the following: Type C_1: "*Anyways, what do you think we should do?*" / "*For instance, we chose 4, and the other team chooses 1, we only get 40 points instead of 70*"; Type C_2: "*I'll do 2*"; Type C_3: "*All right. 1 then*; Type C_4: "*Hey, Guys*".

[21] Another way to explore the dynamics of teams and individuals is to examine their first-period decisions and how decisions in later periods responded to previous history. Appendix A.2 presents the results of such analysis. We focus on the EWA model because it offers a more comprehensive view of dynamic behavior. For instance, when using simpler reduced-form analysis of coordination dynamics, the researcher must specify (1) how many past periods to consider, (2) which past decisions to include (e.g., others' minimum choices, one's own past choices, or both), and (3) how to characterize the current period's variables (e.g., treating the current choice in period t as an ordered or a binary variable relative to previous minimum choices). In our experiment, the presence of a "no-agreement" outcome adds an additional layer of complexity. In contrast, the EWA model integrates all these factors within a single framework, avoiding the need to juggle multiple reduced-form specifications.

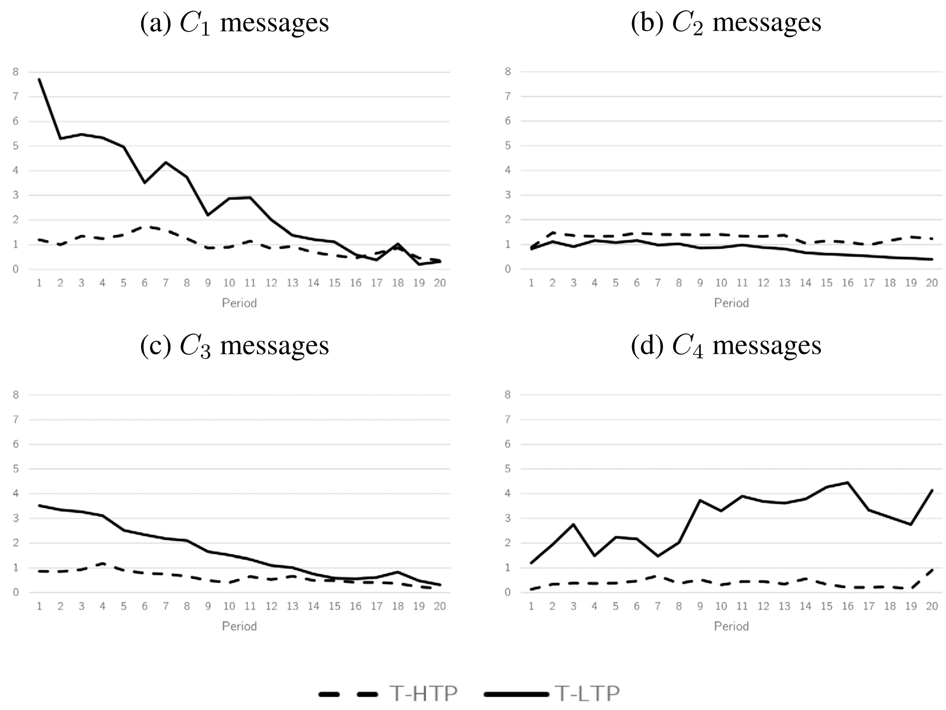

Fig. 2. The average number of messages in each category over 20 periods.

During the course of EWA learning, strategies possess attraction levels that are updated based on two types of payoffs: (i) the actual payoffs resulting from the chosen strategies, and (ii) the payoffs resulting from other strategies. These attraction levels are adjusted in each period based on the cumulative experience gained by the players. Ultimately, the attractiveness of a strategy influences the probability of it being chosen, with more attractive strategies being chosen more frequently.

An overview of the EWA learning model The players (individuals or team) are indexed by i, $i \in \{1, 2, \dots, n\}$; each one has a strategy space $S_i = \{s_i^1, s_i^2, \dots, s_i^m\}$. Let $S := S_1 \times S_2 \times \cdots \times S_n$, where s_i denotes a pure strategy of player i. There are eight pure strategies, i.e., $m = 8$, including choosing number 1 to 7 and doing nothing due to no agreement. In period t, player i's actual decision is denoted as $s_i(t)$ and the relevant order statistic (the minimum effort in the group) is denoted by $z(t)$. The payoff function is $\pi_i\left(s_i^j, z(t)\right) \in \mathbb{R}$, which is the payoff i receiving for playing s_i^j given the relevant order statistic $z(t)$.

For unit i strategy j in period t has a numerical attraction $A_i^j(t)$, which determines the probability of choosing strategy j in period $t+1$ by the following logistic function:

$$P_i^j(t+1) = \frac{e^{\lambda A_i^j(t)}}{\sum_{k=1}^m e^{\lambda A_i^k(t)}}.$$

The parameter λ captures players' sensitivity towards differences among attraction levels. That is, if $\lambda = 0$, the differences are completely ignored and subsequent strategies are chosen randomly with equal probability. As λ increases, probabilities of choosing each strategy converge to the ones in the best response function in which the strategy with the highest attraction is selected. These attraction levels are adjusted each period according to the following equation:

$$A_i^j(t) = \frac{\phi N(t-1) A_i^j(t-1) + \left(\delta + (1-\delta) I\left(s_i^j, s_i(t)\right)\right) \hat{\pi}_i\left(s_i^j, z(t)\right)}{N(t)},$$

where $N(t)$ is a weight on the past attractions following the updating rule $N(t) = \phi(1-\kappa) \times N(t-1) + 1$.[22] The parameter ϕ is interpreted as the depreciation of past attractions, $A(t)$, the degree to which players realize other players are adapting. Intuitively, it can sometimes be interpreted as forgetting. The parameter κ determines the growth rate of attractions, which is also related to the convergence of play. Psychologically, k measures the extent to which players "explore" by trying different strategies relative to how quickly they "exploit" what they have learned.

[22] The original paper of Camerer and Ho (1999) formulate $N(t)$ equivalently as $N(t) = \rho N(t-1) + 1$, where $\rho = \phi(1-k)$. Subsequent EWA literature typically adopts our form, since the parameter k has specific relevance in some applications (see discussions in Ho et al., 2001).

$I(x, y)$ is an indication function, which is equal to zero if $x \neq y$ and one if $x = y$. $\hat{\pi}_i\left(s_i^j, z(t)\right)$ is the actual payoff $\pi_i\left(s_i(t), z(t)\right)$, when $s_i^j = s_i(t)$ and it is the foregone payoffs otherwise.[23] Variables $N(t)$ and $A_i^j(t)$ have initial values $N(0)$ and $A_i^j(0)$, respectively, reflecting pregame experience.

The parameter δ determines how players weigh foregone payoffs relative to actual payoffs. When $\delta = 0$, the model essentially reduces to a pure reinforcement framework, meaning players rely solely on realized payoffs from their own past choices and do not consider the likelihood of other players' future actions.[24]

Let us recall and provide interpretation for five key parameters that govern the EWA learning model: λ, ϕ, κ, δ, and $N(0)$. The parameter λ determines how sensitively decision makers respond to changes in updating attraction for each action via the logit rule. The "attractiveness" of an action is shaped by the learning dynamics captured by the remaining parameters. Specifically, $N(0)$ reflects the strength of prior beliefs before the game begins. The parameter δ controls learning from unchosen actions. The parameter ϕ sets the rate at which players forget past experiences. Finally, κ indicates whether players stick to previously successful options or explore new high-payoff actions.

The maximum likelihood method is used to estimate model parameters. To ensure model identification, we impose necessary restrictions on the following parameters: $\lambda, \phi, \kappa, \delta$, and $N(0)$.[25] Then, for each treatment and game, we estimate initial attractions as described by Ho et al. (2008).[26] The likelihood function to estimate is given by:

$$L(\lambda, \phi, \delta, \kappa, N(0)) = \prod_{i=1}^{6}\prod_{j=1}^{5}\left[\prod_{t=1}^{20} P_i^{s_{i,j}(t)}(t)\right].$$

EWA estimation results In Table 7, we present the estimates for $\lambda, \phi, \delta, \kappa$, and $N(0)$ for each treatment. First, the estimations for λ and δ highlight noticeable differences when comparing teams to individuals under high and low time pressure. In particular, teams under low time pressure exhibit a significantly higher value of λ compared to their individual counterparts. By contrast, teams under high time pressure show a lower value of λ relative to teams under low time pressure. Moreover, the estimate of λ for teams under high time pressure is much more volatile, as indicated by a more than 20-time increase in standard error. Additionally, in the *T-HTP* treatment, teams exhibit an exceptionally small δ compared to other treatments. Finally, there is no statistically significant difference in ϕ across treatments.

Recall that the higher value of parameters λ and δ suggests that teams or individuals choose more optimally based on the attraction of each option, leading to less miscoordination and quicker equilibrium settlement. Our reduced-form evidence shows that teams exhibit lower miscoordination than individuals under low time pressure but not under high time pressure. Additionally, consider that a "no-agreement" outcome due to miscoordination is also a low-payoff choice since the payoff from any other agreement would exceed zero. The observed differences in λ and δ across treatments discussed above align with the reduced-form findings.

We find that teams, regardless of whether they are under low or high time pressure, consistently exhibit a significantly high N_0. N_0 represents the strength of initial attractions relative to incremental changes in attractions due to actual experience and payoffs. This suggests that teams have a greater tendency to make initial choices in later periods. Given that teams begin by selecting high-effort strategies in the very first period, a higher N_0 in our structural estimation indicates a continued preference to maintain high-effort choices in subsequent periods. These estimated parameter results thus align with the reduced-form evidence, which shows that teams consistently choose high-effort numbers over 20 periods, irrespective of time pressure.

6. Conclusions

Our study builds on the experimental design of Feri et al. (2010) to examine how time pressure affects team decision-making in coordination settings. Our findings reveal that time pressure significantly reduces the performance gap between teams and

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[23] When teams do not reach an agreement, they are not informed about the other teams' decisions; thus, the forgone payoffs from unchosen strategies are unknown. Here, we apply the method proposed by Ho et al. (2008)—using the average payoff of the set of possible foregone payoffs conditional on others' strategies to estimate the foregone payoff from unchosen strategies.

[24] For instance, consider a scenario where a player expects that others will choose a minimum effort level of 4 in the future, making 4 the optimal choice moving forward. However, if a past choice of 5 happened to yield the player's highest payoff, the player — under $\delta = 0$ — would continue choosing 5 simply because it has previously yielded a higher payoff, even if that choice no longer aligns with current expectations about others' behavior.

[25] Following Camerer and Ho (1999), we have $\lambda \in [0, \infty], \phi, \delta, \kappa, \in [0, 1]$, and $N(0) \in \left[0, \frac{1}{1-(1-\kappa)\phi}\right]$.

[26] A typical approach in the literature is to estimate initial attractions (common to all players) from the first period of actual data. Formally, define the first-period frequency of strategy j in the population as f^j. Then initial attractions are recovered from the equations

$$\frac{e^{\lambda A^j(0)}}{\sum_k e^{\lambda A^k(0)}} = f^j, j = 1, \ldots, m.$$

This is equivalent to choosing initial attractions to maximize the likelihood of the first-period data for a value of λ derived from the overall likelihood-maximization. The initial attractions can be solved as a function of λ by

$$A^j(0) - \frac{1}{m}\sum_j A^j(0) = \frac{1}{\lambda}\ln\left(\tilde{f}^j\right), j = 1, \ldots, m,$$

where $\tilde{f}^j = f^j / \left(\Pi_k f^k\right)^{1/m}$ is a measure of relative frequency of strategy j. Following Ho et al. (2008), we fix the strategy j with the lowest frequency to have $A^j(0) = 0$ (which is necessary for identification), and solve for other attractions as a function of λ and the frequencies $\tilde{f}^j$.

Table 7
Parameter estimates of EWA learning model.

	T-LTP	T-HTP	I-LTP	I-HTP				
	(1)	(2)	(3)	(4)	(1) v.s. (3)	(1) v.s. (2)	(2) v.s. (4)	(3) v.s. (4)
λ	4.769	4.313	2.824	2.697	***	#	#	#
	(0.180)	(4.008)	(0.456)	(0.846)				
ϕ	0.694	0.659	0.743	0.735	#	#	#	#
	(0.013)	(0.161)	(0.129)	(2.304)				
δ	0.631	0.001	0.628	0.625	#	**	#	#
	(0.042)	(0.259)	(0.040)	(0.789)				
κ	0.619	0.170	0.990	0.990	#	#	#	#
	(0.071)	(0.646)	(0.335)	(0.571)				
$N(0)$	1.111	2.902	0.292	0.168	***	***	***	#
	(0.018)	(0.348)	(0.186)	(0.586)				

Note: (1) λ refers to sensitivity to different attraction levels; ϕ captures depreciation of past attractions; δ denotes the weight placed on forgone payoffs; κ is growth rate of attractions that relates speed of convergence; $N(0)$ is the strength of initial attractions. (2) Numbers in parentheses indicate standard errors. (3) # indicates non-significance at conventional statistical levels, while *,** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

individuals. We identify two key sources of efficiency losses: teams under high time pressure experience more miscoordination and reach fewer agreements than those under low time pressure. Additionally, analysis of intra-team chat logs shows that time-constrained teams engage less in discussions related to learning and teaching about the payoff structure and other components of the environment.

The impact of time pressure on communication differs from other constraints studied in the literature. Charness et al. (2020) examine how communication costs influence a leader's effectiveness in solving logic puzzles and critical thinking problems. They find that imposing messaging costs filters out low-quality messages, improving performance by reducing incorrect suggestions to the leader. In contrast, our study finds that time pressure eliminates high-quality messages, specifically, those related to learning and teaching. These messages could help teams develop a shared understanding of the game and, perhaps more importantly, build trust that other teams also have a strong understanding, thereby reducing strategic uncertainty. This distinction highlights the importance of considering how different communication constraints, whether cost-based (which filter out low-quality messages in logic-based tasks) or time-based (which reduce high-quality messages in a coordination game), affect the performance gap between teams and individuals.

Our findings have direct implications for organizations and decision-making in high-pressure environments. Many workplaces assume that teams naturally outperform individuals, but our results suggest that time constraints can disrupt coordination and weaken the benefits of teamwork. Managers should recognize that under high pressure, teams may struggle to communicate effectively, leading to inefficient decision-making. Our study has shown that team communication plays a crucial role in enabling teams to outperform individuals. Therefore, this mechanism should be taken into account when designing team structures that lead to good team outcomes under time pressure.

There are several avenues for further research on the effects of time pressure on team performance. First, future studies could examine how time pressure interacts with different agreement rules and modes of communication within teams. Exploring alternative decision-making frameworks could identify which team structure mitigates the negative effects of time constraints. The mode of communication, whether one-on-one with the leader, team-wide chat, or face-to-face, may significantly alter how time constraints impact team performance. For example, text-based communication could slow coordination due to delays in message exchanges, while face-to-face discussions may allow for faster consensus-building but introduce additional cognitive load under pressure or reduced interaction. Second, it would be valuable to investigate how teams with an assigned leader perform under time pressure. One possibility is that such teams may simply reflect the leader's individual choices when decisions are made quickly. Additionally, it would be interesting to consider an endogenous leadership framework, where team members have the opportunity to emerge as leaders. In this setting, tighter time constraints might not necessarily harm team performance if the increased pressure encourages the emergence of leaders who can facilitate agreement.

Declaration of competing interest

The authors declare that they have no relevant or material financial interests that are related to the research described in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jebo.2025.107170.

Data availability

Data will be made available on request.

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