# Implicit Coordination Strategies for Effective Team Communication

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**Objective:** We investigated implicit communication strategies for anticipatory information sharing during team performance of tasks with varying degrees of complexity. We compared the strategies used by teams with the highest level of performance to those used by the lowest-performing teams to evaluate the frequency and methods of communications used as a function of task structure.

**Background:** High-performing teams share information by anticipating the needs of their teammates rather than explicitly requesting the exchange of information. As the complexity of a task increases to involve more interdependence among teammates, the impact of coordination on team performance also increases. This observation motivated us to conduct a study of anticipatory information sharing as a function of task complexity.

**Method:** We conducted an experiment in which 13 teams of four people performed collaborative search-and-deliver tasks with varying degrees of complexity in a simulation environment. We elaborated upon prior characterizations of communication as implicit versus explicit by dividing implicit communication into two subtypes: (a) deliberative/goal information and (b) reactive status updates. We then characterized relationships between task structure, implicit communication, and team performance.

**Results:** We found that the five teams with the fastest task completion times and lowest idle times exhibited higher rates of deliberative communication versus reactive communication during high-complexity tasks compared with the five teams with the slowest completion times and longest idle times ($p$ = .039).

**Conclusion:** Teams in which members proactively communicated information about their next goal to teammates exhibited improved team performance.

**Application:** The findings from our work can inform the design of communication strategies for team training to improve performance of complex tasks.

**Keywords:** team collaboration, communication analysis, task complexity, implicit communication, deliberative communication

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## INTRODUCTION

In order for team members to successfully work in concert to achieve a goal, the team must establish a common understanding of the task expectations and communicate effectively (Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000). Results from previous studies have shown that high-performing teams coordinate effectively by sharing information before it is needed, rather than explicitly requesting teammates to perform actions or exchange information (Crant, 2000; Entin & Entin, 2000; Entin, Entin, & Serfaty, 2000; Entin & Serfaty 1999; Shah & Breazeal, 2010; Yin, Miller, Loerger, Yen, & Volz, 2000). However, less is known about which types of anticipatory information sharing are most effective. Our goal in this work was to investigate communication patterns based on the structure of a given task to further determine which types of information sharing relate to efficient team performance.

First, we present a short review of literature that evaluated effective team coordination strategies employed by human teams. Next, we describe studies that aimed to understand and define task complexity, providing insight into the ways that task structure can affect communication. We then propose a set of hypotheses intended to empirically characterize the relationship between task structure, anticipatory information sharing, and team performance. Next, we describe an empirical study designed to evaluate these hypotheses, wherein 13 teams of four participated in a collaborative search-and-deliver task. We analyze the communication patterns that emerged from this study to determine which anticipatory communication strategies were most effective for tasks with varying levels of complexity. Finally, we point to the possible implications of these results for team training and human-robot teams.

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## Communication Strategies to Improve Team Performance

Studies have shown that teammates who primarily exchange information by anticipating one another's needs perform better than those who use less anticipatory communication (Entin & Serfaty, 1999; Entin et al., 2000; Shah & Breazeal, 2010). This type of anticipatory information sharing is referred to as "implicit" coordination. In contrast, "explicit" coordination, which involves prompts or requests for information amongst teammates, corresponds with increased communication overhead (Entin & Serfaty, 1999; Entin et al., 2000; Shah & Breazeal, 2010).

As is noted in prior work (e.g., Hoeft, 2006), there are varying definitions for the term "implicit coordination." One study defined implicit coordination as acting "without consciously trying to coordinate" (Espinosa, Lerch, & Kraut, 2004), whereas another study defined it as the "ability of team members to act in concert without the need for overt communication" (MacMillan, Entin, & Serfaty, 2004). Despite the inconsistencies in definition, each study demonstrated an association between implicit coordination and improved team performance (Espinosa et al., 2004; Hoeft, 2006; MacMillan et al., 2004). In this article, we define implicit and explicit communication as in Entin and Serfaty (1999): Implicit coordination "relies on anticipation of the information and resource needs of the other team members," and explicit coordination is defined as "the transfer of information and resources in response to requests." Communication overhead is associated with the exchange of information, which can require time and cognitive resources (MacMillan et al., 2004). As time pressure increases, teammates who shift their primary coordination and information-seeking strategy to implicit coordination perform tasks faster than those who use explicit coordination (Entin & Serfaty, 1999; Shah & Breazeal, 2010). Increased use of implicit coordination also correlates with a reduced error rate during tasks with a heavy workload (Entin & Serfaty, 1999).

Prior work has studied the use of implicit coordination behaviors and communication efficiency through analysis of the ratio of total communications to communication requests, referred to as the "anticipation ratio" (Entin & Serfaty, 1999; MacMillan et al., 2004). Anticipation ratio values greater than one indicate that team members sent ("pushed") larger amounts of anticipatory information than requested information ("pulled"), thereby reducing communication overhead (Entin & Serfaty, 1999; Entin et al., 2000; Entin, Serfaty, & Deckert, 1994; Hoeft, 2006; MacMillan et al., 2004).

Prior work has also shown that increased communication can lead to an overload of information (MacMillan et al., 2004). It may be beneficial to understand whether there are any specific communication behaviors within implicit coordination that can maintain or improve team performance while reducing the amount of communication needed among team members.

Results from one study conducted with autonomous agents indicated that team members who exchanged information about their intentions while performing a task (i.e., where an agent is going and what they will do upon arriving there) performed better than teams that shared information related to the world state (i.e., where the agent is currently located) (Harbers, Jonker, & Van Riemsdijk, 2012). Although the researchers observed team performance during tasks of varying degrees of complexity, the study was conducted in a virtual environment with simulated agents. Consequently, the results and lessons may not translate to relevant insights into communication strategies for human team members. In addition, the study did not specifically explore implicit communication, but rather communication that was related more generally to the agent's intentions or world knowledge. An empirical study observing human teams as they perform tasks of varying complexity is necessary to determine which specific types of implicit communication strategies are effective for human teams.

In our work, we study two specific types of implicit communication strategies (1) *deliberative communication*, which conveys information related to goals; and (2) *reactive communication*, which conveys information related to the world state and is triggered by a change in the environment. Definitions and examples of both types of communication are provided in the Dependent Measures section.

## Task Complexity

Through previous research, we know that task complexity can negatively affect team performance (Kerr & Tindale, 2004; Klein,

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Feltovich, Bradshaw, & Woods, 2004; Weingart, 1992). Specifically, as task complexity increases to involve more interdependence among teammates, the impact of coordination on team performance also increases (Cheng, 1983; Johnson, 2014). Nonetheless, human teams are often able to effectively perform complex tasks requiring interdependent action if the team members communicate effectively. In this work, we characterized task complexity using the construct developed by Wood (1986) and evaluated the task-specific attributes contributing to a detriment in performance. In addition, we aimed to identify the specific types of implicit communications associated with team performance as task complexity increases.

Task complexity can be defined according to three main attributes: component complexity, coordinative complexity, and dynamic complexity (Naylor & Schenck, 1968; Oeser & O'Brien, 1967; Wood, 1986). *Component complexity* refers to the number of distinct acts and information cues that must be processed to perform a given task. *Coordinative complexity* is defined by the sequencing of information cues and acts as it relates to task performance. *Dynamic complexity* refers to changes to coordinative and component complexity over the course of the task. Our investigation focused on the ways in which component and coordinative complexity impact team performance and communication patterns.

In prior work, team communication for task planning increased when the most complex task required sequencing between actions (coordinative complexity) (Weingart, 1992). However, in contrast to our study, this earlier work did not address communication and coordination on the fly, but only during a preplanning phase. Another study examined strategies for effective coordination of organizations in company management (Malone & Crowston, 1994). The researchers determined that increased coordinative complexity related to increased interdependency between agents and that the study of task complexity and its effect on communication is pertinent to supporting effective group coordination.

## OBJECTIVE

The objective of this study was to present teams with tasks of increasing complexity and compare the communication strategies employed by the teams that best performed a given task to the strategies employed by the worst-performing teams for that task. Our aim was to classify effective communication strategies that teams can adopt during the conduct of tasks with varying degrees of complexity.

*Hypothesis 1 (validation of previous studies)*: We aim to replicate a set of results from prior studies, which found that implicit coordination behaviors were associated with improved team performance (Entin et al., 1994, 2000; Entin & Serfaty, 1999; MacMillan et al., 2004; Shah & Breazeal, 2010).

*Hypothesis 1a*: High-performing teams exchange implicit communications at higher rates than low-performing teams.

*Hypothesis 1b*: Low-performing teams exchange explicit communications at higher rates than high-performing teams.

*Hypothesis 1c*: High-performing teams exhibit a greater anticipation ratio than low-performing teams.

*Hypothesis 2*: High-performing teams will exhibit increased use of communications related to coordinative complexity, or "deliberative communication." In dynamic environments with excessive workload and time pressure, prioritizing the exchange of information can reduce communication overhead (Mathieu et al., 2000). Use of deliberative communication, which prioritizes information about the next goal to be accomplished during a task, can be one way to mitigate the effects of information overload.

*Hypothesis 2a*: High-performing teams will use deliberative communications at higher rates than low-performing teams.

*Hypothesis 2b*: Low-performing teams will use reactive communications at higher rates than the high-performing teams.

## METHOD

We conducted a study involving multiple teams of four people. The teams performed four search-and-deliver tasks within a synthetic task environment (STE) (Salas, Cooke, & Rosen, 2008) called "Blocks World for Teams" (BW4T) (Johnson, Jonker, Van Riemsdijk, Feltovich, &

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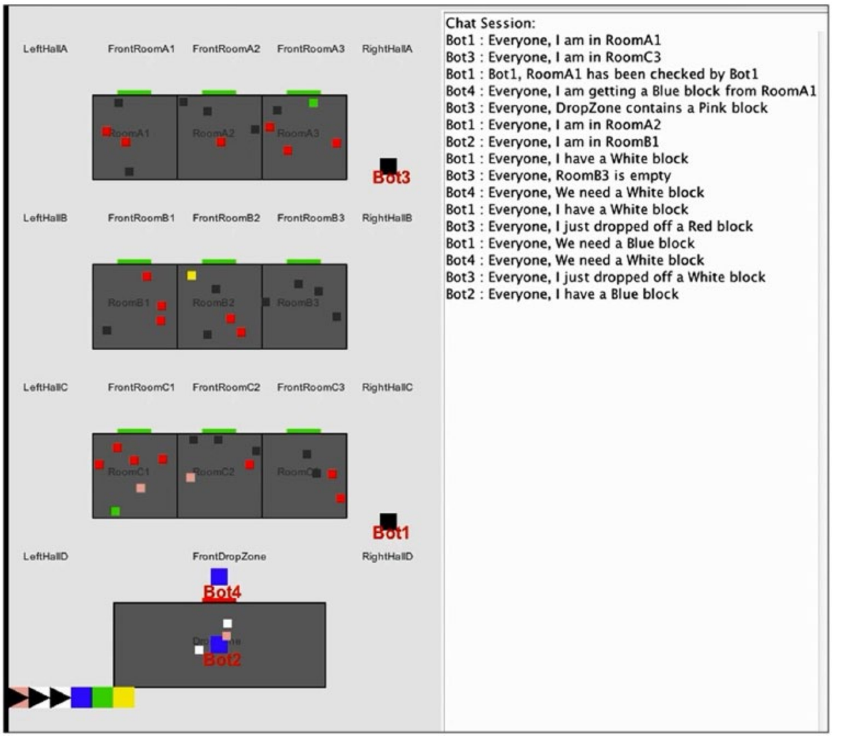


*Figure 1.* The experimenter's view of the task.

Bradshaw, 2009). The objective of each task was to search for and deliver a specified series of colored blocks as quickly as possible.

### Participants

Thirteen teams participated in the study. All participants (41 males and 11 females) were recruited from the Massachusetts Institute of Technology (MIT) and the Greater Boston area and had an average age of 25 years (*SD* = 6.7). Out of the 52 participants, 24 were undergraduate students, 16 were graduate students, and 12 were working professionals. Participants were asked to report whether or not they were color-blind. None of the participants stated that they were color-blind. Each participant received a $10 monetary compensation for their participation in the experiment. An additional monetary incentive of $40 was provided for the team with fastest completion time across all performed tasks. All participants were treated ethically as determined by the MIT Committee on the Use of Humans as Experimental Subjects (COUHES).

### Blocks World for Teams

Implemented in Java, the BW4T testbed allows for human-human, agent-agent, or human-agent teams of varying sizes to work together to complete a search-and-deliver task. BW4T has been widely used within multiagent systems and human-robot interaction communities to better understand the behavior of teams involving human and autonomous agents (e.g., Harbers, 2011; Harbers et al., 2011; Johnson et al., 2012).

*Map environment*. An overview of BW4T is provided through the experimenter's view of the map environment in Figure 1. In our experiment, the environment contained nine rooms, designated A1 through C3, with each room containing colored blocks. A 10th room, designated the "drop zone," was located at the bottom of the map. Participants were tasked with delivering specified colored blocks to the drop zone. The sequence of colored blocks to retrieve during each task was depicted below the drop zone. In addition to the 10 rooms, the environment

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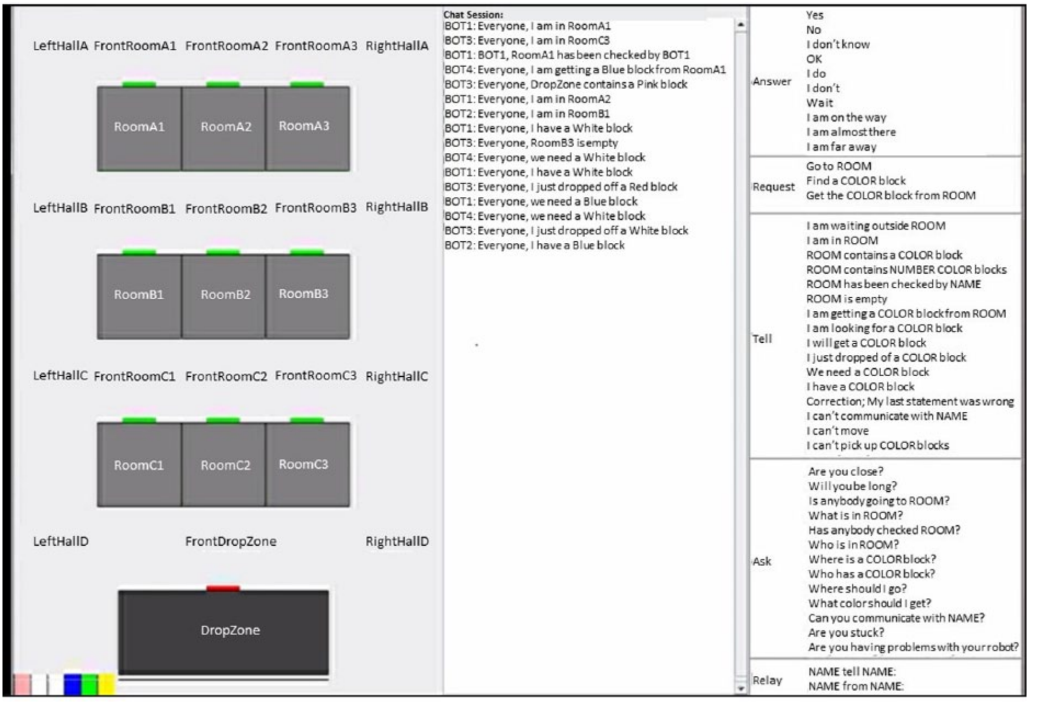


*Figure 2.* A participant's view of the high-complexity task.
*Note.* Font size in the map area is enlarged for readability.

also contained hallways allowing agents (BOTs) to travel from room to room.

Each participant was required to perform a set of actions within the environment to successfully complete the task. To move a BOT, a participant right-clicked anywhere in the environment (i.e., rooms or hallways) and then selected "go here" from a menu of options that subsequently appeared. To pick up a block, a participant entered a room using his or her BOT and typed the first letter of the block color (e.g., "b" for a blue block or "r" for a red block). The participant then entered the drop zone and typed the letter "d" to successfully deliver the block. If the participant delivered a block into the drop zone that was not of the requested color, this incorrect block was automatically and randomly placed into one of the other nine rooms.

*Field of view*. Several constraints were imposed within the interface in order to limit the visual range of each participant, as shown in Figure 2. Each participant could only see the blocks in the room he or she was currently occupying, including the drop zone. Participants were also unable to see the locations of their teammates; however, each room contained a door that provided information as to whether adjacent rooms were occupied: When another agent was occupying an adjacent room, the door to that room was colored red ("DropZone" in Figure 2); otherwise, it was colored green (Room A1 through C3 in Figure 2).

In addition to the field-of-view constraints imposed within the simulation, we also physically restricted participants' view of their teammates. For example, we placed large boards between all four participants to prevent them from seeing one another during the experiment. We also asked all participants to remain silent over the course of the session.

*Communication*. To work effectively as a team and complete the task as quickly as possible, teammates were required to communicate their actions to one another. The BW4T interface included a large chat window and a set of predetermined communications to facilitate this interaction: "Ask," "Question," "Tell," and "Relay." Participants were able to communicate with all of

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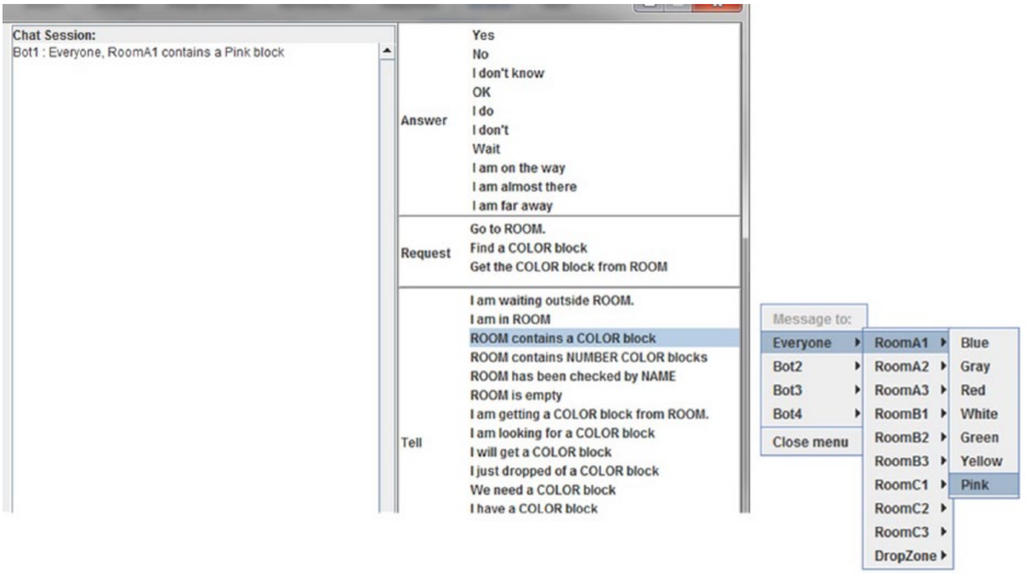


*Figure 3.* Communication structure to send messages in the BW4T interface.

their teammates simultaneously or with individual team members using the communications available to them in the interface. For example, when participants clicked on a communication, a drop-down menu was available to them to send the message to a specific participant ("BOT1," "BOT2," "BOT3," and "BOT4") or "Everyone" to broadcast the message globally. When participants clicked on a communication message that had a bolded item (e.g., "ROOM," "BLOCK"), a multilevel drop-down menu appeared. This allowed participants to first select the participant to whom they want to send the message, then room or block identification information as shown in Figure 3.

Communication was crucial to efficient task performance, as it allowed participants to inform their teammates of their observations and actions. For example, for participants to know which blocks had already been delivered, they could either visit the drop zone, which would be time-consuming, or receive communications from their teammates conveying this information.

## Independent Variable

A within-subject experiment design was employed in which participants completed four tasks at varying levels of complexity: one "low-complexity task," one "high-complexity task," and two "medium-complexity tasks." The medium-complexity tasks were identical, except that one incorporated a "communication failure" in which two of the four agents were unable to communicate with each other for a prespecified duration within the task. Study and analysis related to lost communication are outside the scope of this article and are not included in this analysis.

Based on the construct of task complexity developed in prior work (Wood, 1986), each task was designed for a specific level of component and coordinative complexity. Component complexity was based on the number of blocks present, and coordinative complexity varied according to the number of different colors represented among the blocks participants were instructed to retrieve. This manipulation of complexity allowed us to investigate how task structure affects team performance and communication patterns. More specifically, this approach enabled us to determine how increasing the complexity of the sequencing of the blocks related to increased task completion time and communication rates compared with increasing the number of blocks.

The number and sequencing of blocks used in each task type was determined through pilot

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**TABLE 1:** Overview of Each Task

| Task Complexity Type | Coloring of Blocks | Number of Blocks | Sequencing of Blocks | Task Allocation |
|---|---|---|---|---|
| Low | One color (blue) | 6 | No sequencing | None |
| Medium | Four colors (pink, green, white, blue) | 16 | Alternate sequencing for two colors (P, G, P, G) and (W, B, W, B). | BOT 1: P<br>BOT 2: G<br>BOT 3: W<br>BOT 4: B |
| High | Five colors (pink, white, blue, green, yellow) | 6 | Predetermined random sequencing (P, W, W, B, G, Y) | None |

testing, with the intention that the tasks be possible to complete in a sufficiently short amount of time to allow enrollment of more than 50 participants. The number of blocks required to complete the low- and high-complexity tasks were identical to those used in prior work (Johnson et al., 2009). The colors of the blocks across all task types were determined according to software constraints, as the program only allowed five unique colors to be present in the interface.

*Low-complexity task*. As shown in Table 1, participants were required to collect six blue-colored blocks during the low-complexity task. This task maintained low levels of both component complexity and coordinative complexity, as depicted in Figure 4.

*Medium-complexity task*. During the medium-complexity task, participants were required to search for and deliver 16 blocks, which were divided into two sequences that could be collected in parallel, as shown in Figure 5. One sequence called for pink- and green-colored blocks in alternating order, while the other required white and blue blocks in alternating order. Each of the four team members was assigned a specific color, such that he or she could only deliver blocks of that specific color to the drop zone. (For example, as shown in Figure 5, BOT 4 was the only participant able to bring green blocks into the drop zone.)

*High-complexity task*. During the high-complexity task, participants were required to collect six blocks in a random sequence of colors that was predetermined during the experiment design phase, as shown in Figure 2. The task complexity condition was designed to be of a high level of coordinative complexity, as we

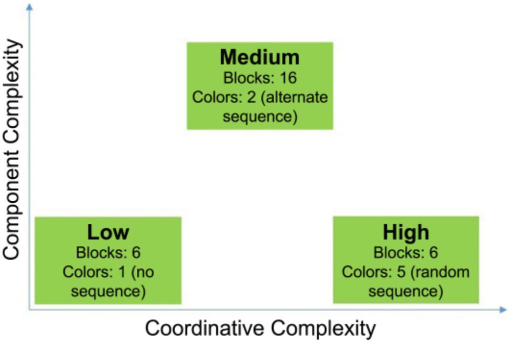


*Figure 4*. Overview of each task based on complexity.

hypothesized that increased coordinative complexity would significantly increase task completion time and communication rates, on average. Although causation cannot be inferred, we confirmed a relationship between task complexity and task completion time, and task complexity and communication rate through two manipulation checks in the results section.

## Dependent Measures

Each coordination behavior exhibited through team communication was classified independently by two researchers according to the matrices presented in Table 2.

*Classification of explicit coordination*. We classified each explicit communication exhibited by team members during task performance based on definitions provided in prior literature. Explicit communications included (a) commands meant to control teammates' future actions and (b)

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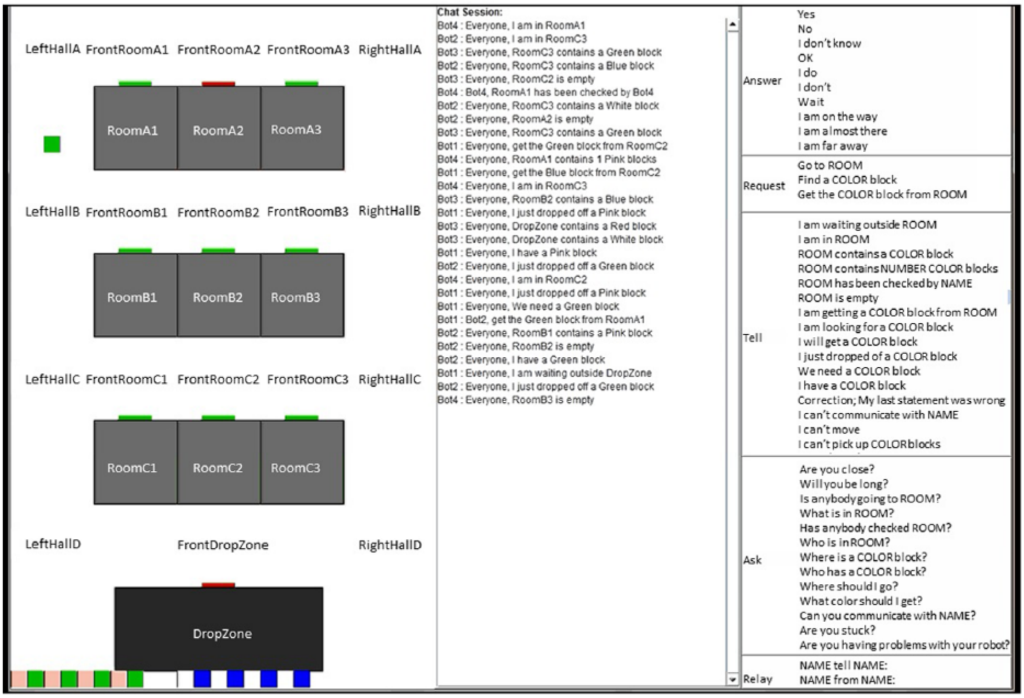


*Figure 5.* A participant's (BOT 2) view of a medium-complexity task.
*Note.* Font size in the map area is enlarged for readability.

**TABLE 2:** Description of Each Coordination Type

| Coordination Type | Subgroup of Coordination Type | Definition | Examples |
|---|---|---|---|
| Explicit coordination | | Commanding other teammates to perform actions; prompting or requesting information from other teammates | -*"Pick up red block from Room A2"* -"Where are you?" |
| Implicit coordination | Deliberative | Information related to next blocks in the sequence (coordinative complexity) | -*"I just dropped off a yellow block"* -*"Room A2 contains a yellow block"* |
| | Reactive | Status updates not pertaining to the next block in the sequence | -*"I am in Room A1"* -*"I am waiting outside of the drop zone."* |

prompts or requests for information (Entin & Serfaty, 1999). An example of explicit communication is depicted in Table 2.

*Classification of implicit coordination*. We classified each implicit communication exhibited by participants while performing the experiment according to definitions provided in prior literature. Implicit communications included the offering of anticipatory information that another teammate might find useful and the communication of status updates about observations (Serfaty, Entin, & Volpe, 1993).

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We coded two additional coordination behaviors, defined as either "deliberative" or "reactive" communication, within the implicit coordination category. Exchanges were coded as "deliberative communication" if the exchanged information related to the next blocks called for in the sequence. Based on this definition, deliberative communications pertained to information related to all the blocks that remained in the sequence to complete the task. For example, if the next blocks in the sequence included a yellow, pink, and green block, communications such as "I have a yellow block," "I have a pink block," or "I have a green block" were considered deliberative and coded accordingly by the experimenters. The classification of deliberative communication requires consideration of the task structure—which, in this experiment, varied with task complexity.

A communication was categorized as "reactive communication" if it conveyed information related to the world state—for example, an agent's position or observation—and was triggered by a change in the environment. Examples include "I am in Room A1" or "I am waiting outside of the drop zone."

Prior to conducting the analysis, each coordination behavior exhibited through team communication was classified independently by two researchers according to the matrices presented in Table 2. This classification was necessary as the communication behaviors were context-dependent. An interrater reliability analysis using the Kappa statistic was performed to determine consistency among raters and yielded Kappa = .89 ($p < .001$), 95% confidence interval (CI) (.83, .94).

## Protocol

The experiment took approximately one hour to complete. Figure 6 depicts a flow diagram of the experiment protocol. First, each participant received an introduction to the study, an informed consent form, and an overview of the BW4T display. This overview consisted of a walkthrough of the display, including instructions on how to communicate using the interface.

Next, participants underwent training sessions, which took approximately 10 minutes to complete. To mitigate learning effect and provide participants with a thorough understanding

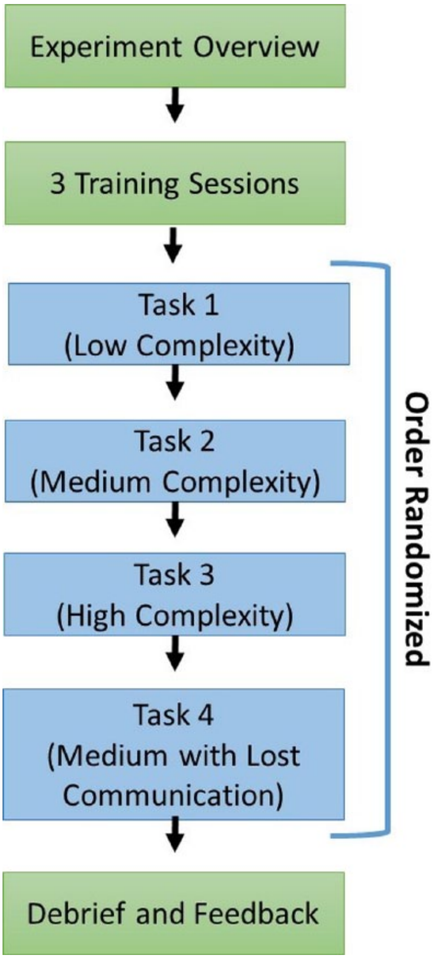


*Figure 6.* Experiment protocol.

of the interface, three training sessions were provided as informed by pilot testing. Participants practiced variations of the low-, medium-, and high-complexity tasks, which were similar to the experiment tasks in structure but different with regard to the color of the blocks. During the first training session, the teams practiced a low-complexity task in which they retrieved six red-colored blocks. Experimenters instructed each participant step-by-step on how to travel between rooms, communicate with team members, and pick up and drop off blocks. Participants completed the second and third training sessions without instruction from the experimenters. In the second and third training sessions, the participants performed variations of the high- and medium-complexity tasks, respectively. Participants were encouraged to use these training

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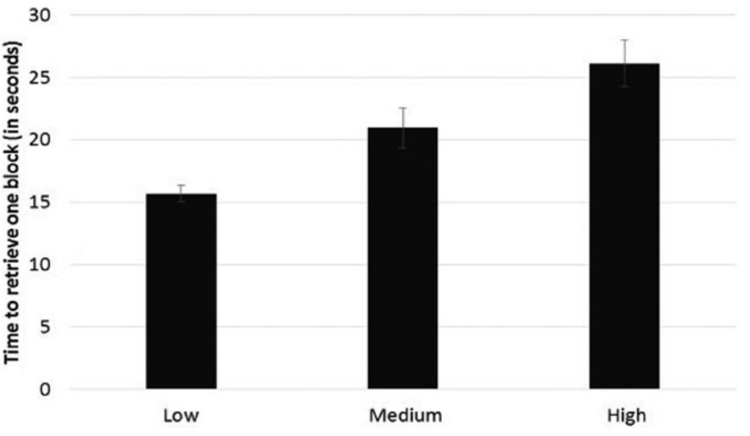


*Figure 7.* Time per block with increasing task complexity.
*Note.* Error bars depict standard error.

sessions to explore the map environment and practice communicating with their team members.

Next, a total of four tasks were executed by the team: one low-complexity task, one high-complexity task, and two medium-complexity tasks. The order of the tasks was randomized to balance for learning and fatigue effects. After completion of each task, a subjective questionnaire was administered in order to obtain feedback on participants' perceived workload, stress, and degree of trust in their teammates.

## RESULTS

In this section, we report findings from the human teamwork experiment. Statistical significance was defined at the $\alpha = .05$ level.

### Measures to Evaluate Team Performance

The team's performance while completing the task was measured in terms of completion time, and this objective was explicitly communicated to participants as part of the experiment protocol. A low task completion time indicated high team performance on the task.

The five teams with the shortest completion times exhibited a significantly lower average idle time per block across all tasks ($M = 5.7$ seconds [s], $SD = 2.7$ s) compared with the five teams with the longest completion times ($M = 10.6$ s, $SD = 5.9$ s) ($p < .01$), according to pairwise *t*-test analysis. Subsequent analysis of communication patterns was therefore conducted by comparing the fastest five teams with the slowest five teams.

### Manipulation Checks

Prior to testing the hypotheses, two manipulation checks were performed to determine the impact of task complexity on team performance and the number of communications.

*Team performance*. The first manipulation check was intended to evaluate the impact of increasing task complexity on team performance. Figure 7 illustrates the differences in the amount of time taken to retrieve one block on average across all 13 teams as a function of task complexity. Using repeated measures analysis of variance (ANOVA), we compared the average time per block during the low-, medium-, and high-complexity tasks and observed a statistically significant difference between the task types, $F(2, 36) = 15.3$, $p < .001$. Results from an additional post-hoc Bonferroni test indicated that the time per block during the low-complexity task ($M = 15.3$ s, $SD = 2.1$ s) was significantly less than that for the medium-complexity task ($M = 20.7$ s, $SD = 5.7$ s). Also, completion of the medium-complexity task took significantly less time than completion of the high-complexity task ($M = 26.3$ s, $SD = 6.4$ s).

These results suggest that an increase in task complexity can have a negative impact on

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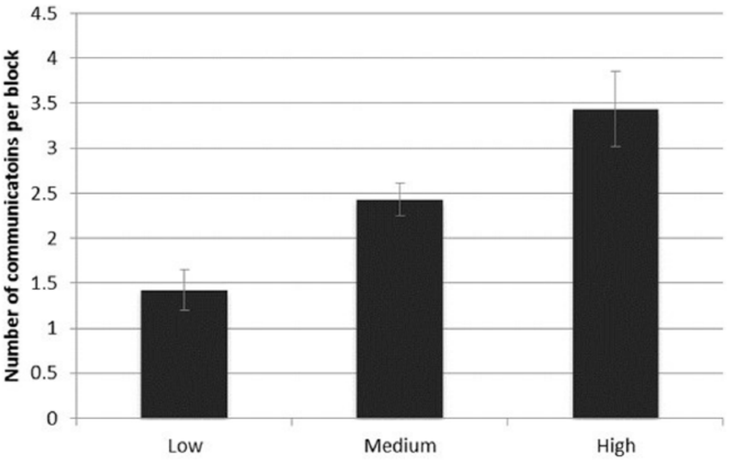


*Figure 8*. Number of communications per block with increasing task complexity.
*Note*. Error bars depict standard error.

performance. Specifically, low complexity with low component and coordinative complexity was associated with faster task execution than medium complexity, which incorporated a high level of component complexity and a low level of coordinative complexity. Medium complexity, on the other hand, was associated with faster task execution than the high-complexity task, which was characterized by a high level of coordinative complexity and a low level of component complexity. These findings suggest that increased coordinative complexity may have a greater negative impact on performance than increased component complexity.

*Number of communications*. The second manipulation check we conducted was to analyze how increasing task complexity impacted the number of communications. Results from repeated measures ANOVA analysis showed that as task complexity increased, the number of communications per block also significantly increased, as depicted in Figure 8, $F(2, 36) = 12.2$, $p < .001$. Results from an additional post-hoc Bonferroni test indicated that the average number of communications per block during the low-complexity task ($M = 1.4$, $SD = 0.80$) was significantly less than that for the medium-complexity task ($M = 2.4$, $SD = 2.4$), which in turn was significantly less than that for the high-complexity task ($M = 3.4$, $SD = 1.4$) as shown in Figure 8.

These findings suggest that teams communicate more frequently as task complexity increases. Low task complexity with low component and coordinative complexity was associated with lower communication rates than medium task complexity with high component and low coordinative complexity. Participants communicated less during the medium-complexity task than the high-complexity task with high coordinative complexity and low component complexity.

## Hypothesis 1: Validation of Previous Studies

Overall, all 13 teams exhibited higher rates of implicit communication ($M = 0.1$, $SD = 0.04$) than explicit communication ($M = 0.01$, $SD = 0.01$). Our Bonferroni analysis (adjusted $\alpha$ level of .017) showed that the five fastest teams exchanged implicit communications at a significantly higher rate than the slowest five teams during both the medium-complexity task, $t(8) = 3.72$, $p < .01$; and the high-complexity task, $t(8) = 3.10$, $p = .013$, as shown in Figure 9. There was no statistically significant difference between the top five and bottom five teams during the low-complexity task.

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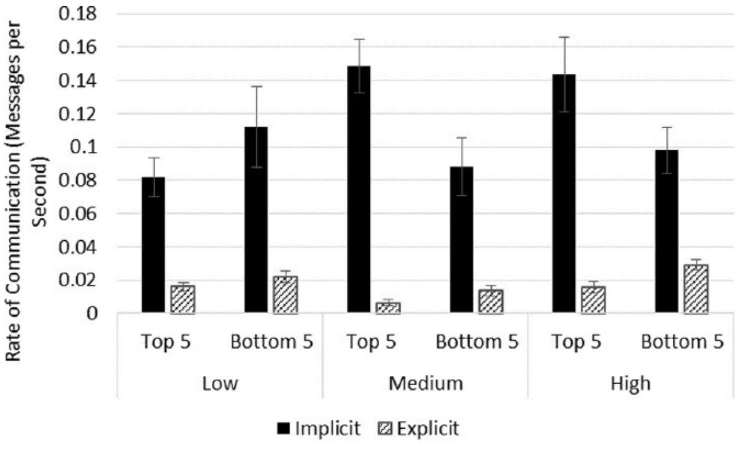


*Figure 9.* Rate of implicit and explicit communications for top five and bottom five teams.
*Note.* Error bars depict standard error.

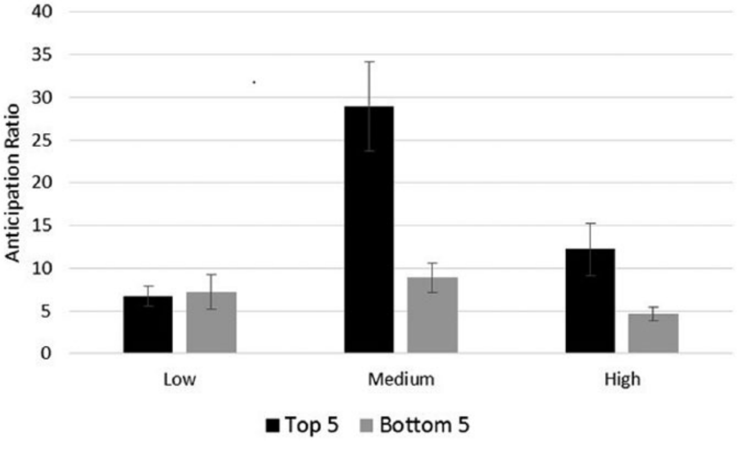


*Figure 10.* Anticipation ratios of top five and bottom five teams.
*Note.* Error bars depict standard error.

We also compared anticipation ratios for the best- and worst-performing teams. Our Bonferroni analysis (adjusted α level of .017) indicated that the five fastest teams exhibited a higher anticipation ratio than the slowest five teams for the medium-complexity, $t(8) = 3.5$, $p < .01$; and high-complexity tasks, $t(8) = 2.93$, $p = .012$, as shown in Figure 10. Our analysis of implicit versus explicit communication, in addition to anticipation ratio, is valuable in that the results indicate that high-performing teams exhibit both an increased rate of implicit coordination and an increased anticipation ratio compared with the low-performing teams.

### Hypothesis 2: Communication Patterns Emerge from Task Structure

We hypothesized that high-performing teams would use deliberative communication more frequently than low-performing teams, and that low-performing teams would exhibit higher rates of reactive communication than high-performing teams. Our Bonferroni analysis (adjusted α level of .017) indicated that the five

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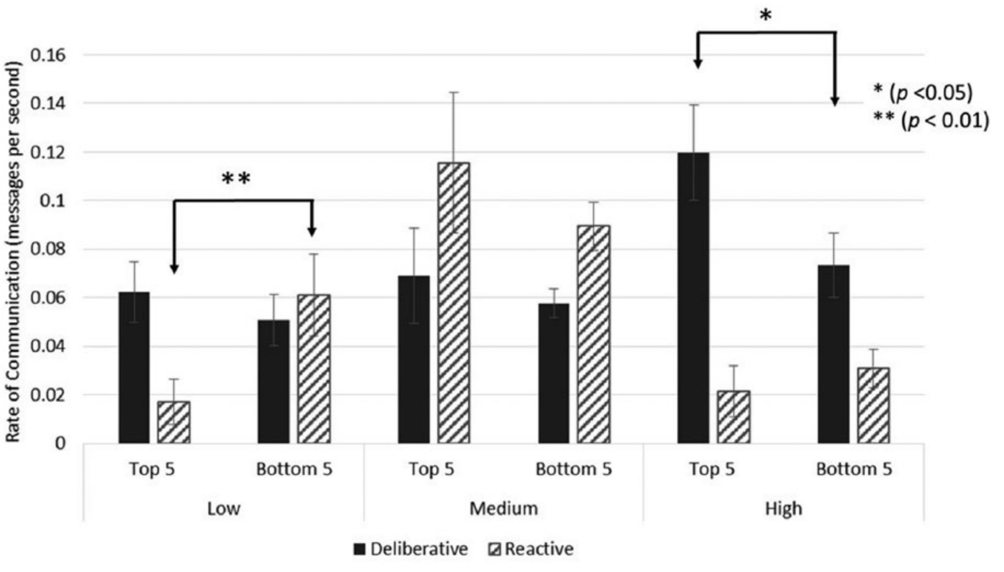


*Figure 11.* Rates of deliberative and reactive communication for top five and bottom five teams.
*Note.* Error bars depict standard errors.

teams with the fastest completion times had significantly higher rates of deliberative communication than the slowest five teams during the high-complexity task, $t(8) = 2.64$, $p = .039$, as shown in Figure 11. In addition, the slowest five teams had higher rates of reactive communication than the fastest five teams and higher rates of status updates regarding the environment during the low-complexity task, $t(8) = 4.56$, $p < .01$.

## DISCUSSION

This study identified effective communication strategies employed by the best-performing teams during an experiment and compared these strategies with those employed by the worst-performing teams. We found that all 13 teams exhibited higher rates of implicit coordination than explicit coordination. This may be due to the fact that, prior to the start of the experiment, the teams trained on the task together and gained enough context for participants to anticipate the needs of their teammates. (Results may have been different if the teams had no experience working together or lacked a common understanding of the task.) Additionally, the top five teams exhibited higher rates of implicit coordination than the bottom five teams during the medium- and high-complexity tasks. Also, as task complexity increased, we observed higher rates of deliberative coordination rather than explicit coordination among the top five teams.

This is an important finding, because it indicates that deliberative communication—a type of implicit coordination behavior—may be particularly beneficial for effective teamwork when performing tasks with high coordinative complexity. One possible explanation for this result is that high-performing teams were able to reduce their communication overhead during more complex tasks by prioritizing the exchange of implicit communication related to the next goal, which was sufficient to maintain coordination among team members. This reduced communication burden may have enabled the team to dedicate additional temporal and cognitive resources to improving task performance. Interestingly, the five teams with the slowest completion times exhibited higher rates of reactive communication during the low-complexity task, possibly indicating that high communication overhead may be detrimental to the performance of simpler tasks as well.

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Empirical evaluation of deliberate versus reactive communication strategies employed by high-performing teams has not been documented by prior work. Ours is the first study to identify that the use of deliberative communication, a subset of implicit coordination, is a critical aspect of communication that is associated with improved team performance. Particularly, when the coordinative complexity of a task is high, prioritizing the exchange of information related to the next goal may reduce communication overhead. One direction that merits future work is to explore the link between deliberative-implicit communication and theories of team cognition (MacMillan et al., 2004; Salas et al., 2008) to determine team members' mutual understanding of each other's roles when performing complex tasks.

### Validation of Total Task Complexity

Prior work has identified three aspects of task structure that contribute to total task complexity: component, coordinative, and dynamic complexity. Our study evaluated component and coordinative complexity, but not dynamic complexity. To evaluate dynamic complexity, the task structure would need to be further modified to incorporate change to the environment or task over time. For example, in the BW4T environment, this change could be simulated by altering the goal (such as the specified sequence of colored blocks) as the task progressed. Evaluating dynamic complexity would provide insight into how a greater degree of uncertainty can impact performance of a task within a complex environment. An empirical study evaluating total complexity could be valuable for identifying coordination strategies to further mitigate communication overhead and improve task performance, particularly with regard to highly dynamic and uncertain tasks.

This work is a first step toward empirical evaluation of task complexity to assess its impact on team performance. We used preexisting BW4T software to simulate tasks with varying degrees of complexity. While the BW4T application can provide face validity, as it is widely used and can replicate a search-and-rescue environment, further external validation that utilizes this approach for other applications is necessary.

### Team Training

This work builds on a longstanding tradition in which insights from applied psychology are translated to develop training programs that enhance team coordination (Ford, Kozlowski, & Kraiger, 1997; Helmreich, Merritt, & Wilhelm, 1999; Salas, Burke, Bowers, & Wilson, 2001). Results from our work may provide guidelines for how teams working in complex environments could be trained to communicate more effectively. For example, we found that the amount of communication increased for all teams as task complexity increased, as shown in Figure 7. However, the best-performing teams communicated using higher rates of deliberate implicit communication, as compared with the worst-performing teams.

Furthermore, our results suggest that training team members to proactively communicate information about their next goal to their teammates could improve team performance. Prior work has empirically evaluated various team training strategies to incorporate effective communication (Salas, Nichols, & Driskell, 2007), such as cross-training (Cannon-Bowers, Salas, Blickensderfer, & Bowers, 1998), self-correction training (Blickensderfer, Cannon-Bowers, & Salas, 1997; Smith-Jentsch, Zeisig, Acton, & McPherson, 1998), team coordination, and adaptation training (Entin et al., 1994). For example, team adaptation training is aimed at altering team coordination strategies to reduce communication overhead (Entin et al., 1994). Future work is needed to determine the appropriate training strategies and whether teams trained to communicate using higher rates of deliberative communication do improve their performance.

## CONCLUSION

This study identified communication strategies employed by teams that best performed an assigned task, as indicated by task completion time and idle time, and compared them with the strategies employed by the worst-performing teams. We found that as task complexity increased, the best-performing teams

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exhibited higher rates of implicit coordination than explicit coordination. Furthermore, these teams also exhibited higher rates of deliberative communication rather than reactive communication as task complexity increased. We gained insight into deliberative communication by evaluating task structure and observed that as sequencing became increasingly complex, communication related to the team's next goal became more valuable to teammates, who were then better able to plan their subsequent actions.

## KEY POINTS

- To evaluate effective team communication strategies, we conducted an empirical study involving 13 teams of four people, where participants performed four search-and-deliver tasks within a synthetic task environment called "Blocks World for Teams."
- We compared the strategies employed by the best-performing teams with those employed by the worst-performing teams as task complexity increased.
- We observed higher rates of implicit communications than explicit communications among the best-performing teams for a high-complexity task. Furthermore, these teams also exhibited higher rates of deliberative communication rather than reactive communication with increasing task complexity.
- The results of our experiment indicate that teams in which members proactively communicated information about their next goal to one another reduced communication overhead and improved team performance.
- The findings from our work can inform the design of communication strategies for team training to improve performance of complex tasks.

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