Choosing the Task Allocator:  
Effect on Performance and Satisfaction in Human-Agent Team

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Abstract
Ad hoc human-agent teams, where team members interact without prior experience with teammates and only for a limited number of interactions, will be commonplace in dynamic environments with opportunity windows for collaboration between diverse groups. We study the efficacy of virtual ad-hoc teams, consisting of a human and an agent, collaborating to complete tasks in each of a few episodes. To maximize team potential, the relative expertise of team members must be measured and utilized in allocating tasks. As team members are not initially aware of each other's task competence and as humans often cannot accurately estimate their competencies, adapting allocation over the episodes is critical to team performance. Human team member satisfaction with allocations is also critical to determining team viability. We therefore use both these criteria to measure the effectiveness of task allocation procedures with varying degree of flexibility and human teammate control: (a) alternating, (b) performance adaptive, (c) agent-guided, (d) human-selected. We report on the relative strengths of these allocation procedures based on results from experiments with MTurk workers.

Introduction
Agents can collaborate with people on critical tasks, such as guiding emergency evacuations (Robinette, Wagner, and Howard 2013) and disaster relief (Ramchurn et al. 2015). Recent intelligent agent applications traditionally assume human roles in human-agent teams, e.g., tutor (Sanchez et al. 2014) and trainer (Lin et al. 2014) in physical (robotic) and virtual settings (Rosenfeld et al. 2017). Since human-agent teams are being recognized as a functionally critical important component of our societies, researchers are studying the interactions and dynamics within these teams to improve their design (Gervits et al. 2020).

We are interested in human-agent collaboration in ad hoc teams where team members do not have prior knowledge or interaction experience with their teammate (Genter, Agmon, and Stone 2011). We consider ad hoc teams that try to accomplish a set of tasks chosen from diverse task types. We assume that different human teammates will have different competence and expertise in various task types. We use a fixed agent expertise distribution (simulated) over a set of task types. To optimize the performance of a given human-agent team, it is necessary to allocate tasks to the team members based on their relative expertise. The allocation problem is challenging because a team member does not have a priori knowledge of the levels of expertise of its partner. Although we allow human and agent partners to share their estimated expertise over different task types, the accuracy and consistency of such estimates expressed by humans are unreliable (Kahneman 2011). Repeated interaction allows partners to refine initial estimates provided, but such opportunities are few because (i) only a limited number of repeated teamwork episodes and (ii) allocation decisions that determine what task types are performed by a partner in an episode. Therefore, success of such ad hoc human-agent teams in completing assigned team tasks will critically depend on effective adaptability in the task allocation process.

We designed four task allocation protocols with various degrees of responsibilities and input from the agent and human team member. We present results from experiments with MTurk workers that involve two relevant metrics, team performance and human satisfaction in teammate, that measure the viability of such human-agent ad hoc teams.

Related Work
Human-agent teams have been studied in many domains including space robotics (Gervits et al. 2020) and decision-making (Anderson, Kleinberg, and Mullainathan 2017). Majority of this work is on agents in supportive roles to humans (Lai and Tan 2019) in both robotic and simulation settings (Rosenfeld et al. 2017). We focus on an ad hoc environment, where some other studies assume interactions with agent and environment prior to the study (Gervits et al. 2020). We are also interested in autonomous agents as a "team member fulfilling a distinct role in the team and making a unique contribution" (Larson and DeChurch 2020).

Task allocation has been extensively studied in multi-agent teams (Korsah, Stentz, and Dias 2013; Mosteo and Montano 2010). In agent teams, the focus is on designing efficient mechanisms for agents to distribute tasks within their society. Task allocation is also studied in the literature on human team and organization (Puranam, Alexy, and Reitzig 2014). However, we are not aware of prior examination of autonomous agents with task allocation roles, compared to humans, in virtual and ad hoc human-agent teams. Any organization must solve four universal problems, including task
Figure 1: CHATBoard showing allocated tasks to teammates.

allocation, to achieve its goals (Puram, Alexy, and Reitzig 2014). The mechanism of task allocation, including capability identification, role specification, and task planning, is considered an important component of teamwork (Mathieu and Rapp 2009). In human teams, the focus is on understanding the characteristics of teams to design the best possible task allocation mechanism. Research on the effect of autonomous agent task allocators on human teams is scarce.

In addition to team performance, human satisfaction is a major facet of team viability (Gladstein 1984). To our knowledge, there has been little investigation of satisfaction in the human-agent team literature.

Collaborative Human-Agent Taskboard (CHATboard)

We present CHATboard, an environment facilitating human-agent, as well as human-human, team collaboration. (see Figure 1). CHATboard contains a graphical interface for displaying assigned tasks to be completed, as well as allocations and performance by team members on assigned tasks. Support multiple task allocation protocols and communication between team members to express confidence levels.

The CHATboard framework allows task postings on blackboards, often used in human teams, to facilitate a human team member perceiving an agent as a distinct team member. We incorporate three task boards in our task sharing frame: one shared board, which includes the set of team tasks organized by type, and two other boards, respectively, for the tasks assigned to the human and the agent team member. These task boards are easily navigable repositories for team information, allowing team members to share and view information through these boards.

We define a set of $n$ team members $N: \{p_1, p_2, ..., p_n\}$, a set of $m$ task types $M: \{y_1, y_2, ..., y_m\}$, a set of $r$ tasks, $T_{jr}: \{t_{j1}, t_{j2}, ..., t_{jr}\}$, for each task type $y_j$. Team member $i$ can share their confidence levels $p_i(y_j)$ over task types $y_j$. The set $C_i: \{p_i(y_1), p_i(y_2), ..., p_i(y_m)\}$ represent confidence levels for different task types for team player, $p_i$. The team members will interact over $E$ episodes, where episode numbers range from $1 \ldots E$. $A_{i,e}$ denotes the set of tasks allocated to player $i$ in episode $e$ and we assume that all available tasks are exhaustively allocated, i.e., $\bigcup_e A_{i,e} = \bigcup_j T_{jr}$.

The performance of player $p_i$ for a task $t_{jk}$ in episode $e$ is referred to as $o_{ijk,e} \in \{0, 1\}$. We define the performance of $p_i$ on task type $y_j$ in episode $e$ as $\mu_{i,yj,e} = \sum_{t_{jk} \in A_{i,e}} o_{ijk,e}$.

Algorithm 1 Turn-taking Allocator Protocol

1: **Input:** $M$, $T$, $E$, $N = \{p_h, p_a\}$
2: $C_h, C_a \leftarrow$ ConfidenceLevels()
3: for $e = 1 \ldots E$ do
4: if $e \mod 2 = 1$ then
5: AssignAllocator($p_h$)
6: **Input:** Task Allocations ($A_{h}^e$)
7: else
8: AssignAllocator($p_a$)
9: **end if**
10: ReceiveTasks($T_{a}^e$)
11: CalculatePerformance($TP_e$)
12: **end for**

Allocation Protocols

Task allocation protocols that automatically assign the human or agent the allocator role have their respective limitations. We designed four new protocols that involve both teammates’ allocation capabilities over a series of episodes.

Turn-taking Allocator Protocol

Turn-taking Allocator Protocol is where the human and the agent take turns for the allocation role (Fig 2). Before the episode starts, team members share their confidence levels for each task type. The human teammate is tasked with allocating tasks in the first episode. For the following episodes, the allocator role is alternated between the human and the agent. Alternating the allocator role aids the team members learn about their partner’s allocation capabilities.

Figure 2: Turn-taking Allocation Protocol.

Performance-based Allocator Protocol

Performance-based Allocator Protocol also allows both team members to allocate tasks (Figure 3). The human and the agent allocates tasks in episodes 1 and 2, respectively ($A_{h}^1$ and $A_{a}^2$). For the remaining episodes, the protocol assigns the allocator role based on average team performance when human ($TP_h$) and agent ($TP_a$) team members are allocating. For any episode after the first two episodes, the team members whose allocation(s) resulted in higher average team performance is selected as the allocator.

Agent Guided Allocator Protocol

Agent Guided Allocator Protocol gives the allocator role to the human for every episode (Figure 4). The agent’s role in this protocol is to provide suggestions in the $n^{th}$ episode to the human before allocation. The agent provides task allocation suggestion, $A_{nh}^e$, to the human by comparing the human teammate’s expressed confidence levels and prior episode.
Algorithm 2 Performance-based Allocator Protocol

1: Input: $M, T, E, N = \{p_h, p_a\}$
2: $C_h, C_a \leftarrow \text{ConfidenceLevels}()$
3: for $e = 1...E$ do
4:   if $e == 1$ then
5:     AssignAllocator($p_h$)
6:     Input: Task Allocations ($A^e_h$)
7:   else if $e == 2$ then
8:     AssignAllocator($p_a$)
9:     else if $TP_h \geq TP_a$ then
10:    AssignAllocator($p_h$)
11:   Input: Task Allocations ($A^e_h$)
12:   else
13:    AssignAllocator($p_a$)
14: end if
15: ReceiveTasks($T_e^h$)
16: CalculatePerformance($TP_e^h$)
17: end for

Algorithm 3 Agent-guided Allocator Protocol

1: Input: $M, T, E, N = \{p_h, p_a\}$
2: $C_h, C_a \leftarrow \text{ConfidenceLevels}()$
3: for $e = 1...E$ do
4:   AssignAllocator($p_h$)
5:   AgentSuggestions($A^e_a$)
6:   Input: Task Allocations ($A^e_a$)
7:   ReceiveTasks($T_e^h$)
8:   CalculatePerformance($TP_e^a$)
9: end for

Hypotheses development

We now motivate and present our research hypotheses related to these task allocation protocols in human-agent teams and their relation to team performance and satisfaction that we will be experimentally evaluating.

Task allocation protocols provide mechanisms for how human and agent teammates to collaborate in completing task assignments. Initial research had shown that when the same allocator was allocated for all episodes, team performance with agent allocators was higher compared to their human counterparts. However, human satisfaction with the teammate was lower when the agent teammate allocated tasks. Our research goal here is to develop, evaluate, and identify protocols that both produce good team performance and human satisfaction with its teammate.

In the performance-based protocol, where the allocator role assignment is adaptive, i.e., to team members who perform better as an allocator, we expect the agent to be chosen as the allocator in most episodes. As agent allocators produce higher team performance, we expect team performance with this protocol to be higher than non-adaptive protocols.

**Hypothesis 1**: The Performance-based protocol will have the highest team performance.

Previous work with agent allocators showed human satisfaction was low as they had less control and input into the task allocation process (Abuhaimed and Sen 2022). Conversely, if the agent teammate does not provide input to the allocation process, human teammates may feel the agent is not contributing. Thus, we expect human satisfaction with agent to be highest when they have higher control while the agent provide guidance.

**Hypothesis 2**: Human satisfaction with the agent will be highest with the Agent-guided protocol.

One way to increase human satisfaction and team performance simultaneously is to give the human teammate more

Human-selected Allocator Protocol

Human Selected Allocator Protocol empowers the human team member with the metalevel decision of choosing the allocator in each episode (Figure 5). Before the start of episode $n$, the protocol asks the human to select the allocator for $n$th episode. If the human member chooses to allocate, they allocate task tasks for the episode ($A^e_h$); otherwise, the agent allocates the tasks ($A^e_a$).

Figure 3: Performance-based Allocation Protocol.

Figure 4: Agent-guided Allocation Protocol.

Figure 5: Agent-guided Allocation Protocol.
control in the allocation decision. The Turn-taking protocol alternates the allocator role between the human and the agent. The Agent-guided Protocol gives human full control, yet the agent can provide input by suggesting optimal task allocations. We do not expect the Turn-taking protocol to produce optimal performance, since the human is responsible of allocating almost half of the time. However, with the Agent-guided protocol, we expect team performance to be higher with optimal allocations suggested by the agent.

**Hypothesis 3a:** Agent-guided protocol will produce higher team performance than Turn-taking protocol.

Moreover, humans like to explore, and we do not expect them to follow all agent recommendations in earlier episodes, but increasingly adopt them in latter episodes.

**Hypothesis 3b:** Human allocators will increasingly follow agent guidance, in the Agent-guided protocol, in later episodes.

Both human satisfaction and team performance can possibly be improved by using the Human-selected protocol, where the human chooses the allocator in each episode. Initial experiments showed that agent allocators produce higher team performance. We expect humans to notice that performance is higher when they select the agent to allocate, and hence assign the allocator role to agent more than themselves.

**Hypothesis 4a:** Human participants will more often select the agent as an allocator than themselves.

If human participants select the agent as an allocator in all episodes, then the performance of the team will be high, but as humans like to explore, we do not expect full utilization of the agent teammate. However, we do expect that the use of agent to allocate tasks increases over later episodes.

**Hypothesis 4b:** The assignment of allocator role to the agent by human participants will be higher in latter episodes.

In the Agent-guided Protocol, the human teammate is assigned allocator and has to choose whether to follow agent suggestions, whereas, in the Human-selected Protocol, human teammate has to select the allocator for respective episode. In the former protocol, the human has the option to not follow all of the agent’s suggested allocations, but in the former, the option is not there. So we expect a slight difference in team performance.

**Hypothesis 4c:** The Human-selected protocol will produce higher team performance than Agent-guided protocol.

Lastly, when comparing the four protocols presented, we find that the Human-selected and Agent-guided protocols have the highest level of control or input, and hence we expect them to have higher human satisfaction than others.

**Hypothesis 4d:** Human-selected and Agent-guided Protocols will have a higher satisfaction than Turn-taking and Performance-based Protocols.

### Methodology

We present details of the team interaction protocol, agent behavior, evaluation metrics, and experiment design.

### Agent Characteristics

**Expertise:** An agent has a fixed profile which specifies its expertise levels for different tasks, represented as a vector of probabilities for successful completion of task types.

**Agent Allocator Strategy:** We assume that each task is allocated to and performed by a single team member and does not require work of multiple individuals, i.e., \(A_i \in \mathcal{E} \cap A_j \in \mathcal{E} = \emptyset \). In this paper, we also require that the number of tasks assigned to each team member be the same, i.e., \( \forall x, y, |A_x| = |A_y| \). However, a different number of tasks can be assigned to two team members for different types of tasks.

The primary allocation goal is to maximize the utilization of team capacity given the expertise of team members and subject to the constraint that team members be assigned equal task loads. The agent uses estimates of human teammates’ task completion rates by task types in the allocation procedure that solves this constrained optimization problem:

\[
\max \sum_{y \in M} (x_y a(y) + (1 - x_y) h(y)); \quad \text{s.t.} \forall y, x_y \in 0, 1,
\]

where \( x_y \) is a binary variable indicating whether a task type, \( y \), is assigned to a human or agent, based on the current performance estimate of the human, \( h(y) \), and agent, \( a(y) \), on task type \( y \). Each team member is assigned exactly half of the task types. The unbalanced assignment problem, where the number of task types is greater than the number of team members (\( m > n \)), can be solved by transforming it into a balanced formulation, e.g., adding dummy variables, and running the Hungarian algorithm (Kuhn 1955). We utilize the SCIP mixed integer programming solver (Perron and Furmon), represented by \texttt{getAllocations()} procedure in Line 6 of Algorithm 5, to find the allocation that maximizes the utilization of team capacity.

In many task allocation formulations, for example, matching markets and assignment problems, participants’ preferences or confidence levels are assumed to be accurately known (Shoham and Leyton-Brown 2008). In our formulation, however, learning is needed as human participant’s expertise is simulated by flipping a coin with success probability of \( \theta \), the confidence level.
Algorithm 5 Agent Allocator Strategy

Input: $N = \{p_i, p_j\}, M = \{y_1, \ldots, y_m\}, E$

1: for $e = 1,..., E$ do
2:     if $e = 1$ then
3:       $Q_{i,j} \leftarrow p_i(y_j), \forall p_i \in N, y_j \in M$
4:     else
5:       $A_{i,e} \leftarrow \text{getAllocations}(Q_{i,e})$
6:     if $y_j$ is allocated to $p_i$ then
7:       $Q_{i,j} \leftarrow (1 - \alpha) \cdot Q_{i,j} + \alpha \cdot \mu_{i,j,e}$
8:     end if
9: end if
10: end for

Figure 6: Instances of different task types.

estimates of their capabilities can be inaccurate. Since this is an ad hoc environment, the second goal of our agent is to quickly learn about its partner’s expertise levels and accordingly adapt allocations for improved team performance. After each interaction, $e$, the agent updates the capability model, $Q_{i,j}$, of team member, $p_i$, for each task type, $y_j$, from the observed performances, $\mu_{i,j,e}$, as follows: $Q_{i,j} \leftarrow (1 - \alpha) \cdot Q_{i,j} + \alpha \cdot \mu_{i,j,e}$. However, in the first episode, the agent allocator explores the capabilities of the team members by partitioning tasks within each task type, $T_{y_j}$, equally between the members, as shown in Algorithm 5, Line 4.

Evaluation Metrics

Team Performance: A task allocated to a team member is completed successfully or a failure is reported. Team overall performance is measured as the percentage of successful completion of assigned tasks over all episodes: Unweighted Team Performance is measured as the average team performance over episodes, $\frac{1}{E} \sum_{e=1}^{E} R_{\text{team},e}$, where $R_{\text{team},e}$ is the team performance in episode $e$, which is the average performance of all team members over all task types in that episode $R_{\text{team},e} \leftarrow \frac{1}{m_m} \sum_{i=1}^{n_i} \sum_{j=1}^{n_m} \mu_{i,j,e}$.

Human Satisfaction: We measure the satisfaction with the agent through satisfaction a survey proposed by (Green and Taber 1980) and (Reinig 2003) with five questions. The survey follows a 5-point Likert scale setting administered at the end of the study. We present a sample question from the survey: “I am satisfied with my agent teammate.”

Table 1: Satisfaction and Performance over Protocols.

<table>
<thead>
<tr>
<th>Protocols</th>
<th>Human Satisfaction</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turn-Taking</td>
<td>3.79</td>
<td>0.74</td>
</tr>
<tr>
<td>Performance-based</td>
<td>3.63</td>
<td>0.76</td>
</tr>
<tr>
<td>Agent-Guided</td>
<td>3.86</td>
<td>0.73</td>
</tr>
<tr>
<td>Human-Selected</td>
<td>3.61</td>
<td>0.74</td>
</tr>
</tbody>
</table>

Experimental configurations

We conducted experiments with teams of one human and one agent ($n = 2$), $N = \{p_a, p_b\}$. We use four task types ($m = 4$), $M = \{y_1, y_2, y_3, y_4\}$, which are Identify Language, Solve WordGrid, Identify Landmark, and Identify Event (examples of task types shown in Figure 6). The task types are selected so that for each type, sufficient expertise variations in recruited human subjects are likely. For example, Identify Language is a task type in which team members are asked to identify the language, e.g. Japanese, from a text from a number of options, e.g. Japanese, German, Hebrew, Arabic.

We created 32 ($r = 8$) task instances for each of four episodes ($E = 4$). We recruited 260 participants from Amazon Turk, 65 for each condition, as recommended for a medium-sized effect (Brinkman 2009). We use a between-subject experimental design, and each team is randomly assigned to a protocol. After participants agree to the Informed Consent Form, they read the study description and start the first episode. Each episode contains three phases: taskwork allocation, taskwork completion, and taskwork results. After each episode, the results are displayed to the human and agent teammates, which include overall and per-type performances. At the end of the four episodes, participants complete a satisfaction survey. We incorporate random comprehension attention checks to ensure the fidelity of the result (Hauser, Paolacci, and Chandler 2019). Participants may receive a bonus payment based on team performance.

Experimental Results

Team Performance: Based on means, Performance-based protocol has the highest performance ($M_p = 0.76, SD_p = 0.07$) of four protocols. However, an ANOVA shows the performance advantage is not statistically significant ($F = 1.2, p > 0.05$). The performance of Agent-guided protocol ($M_p = 0.73, SD_p = 0.06$) is slightly lower than Turn-taking protocol ($M_p = 0.74, SD_p = 0.07$) and a t-test shows this difference is not statistically significant ($t = 0.5, p > 0.05$). The performance of the Human-selected protocol ($M_p = 0.74, SD_p = 0.05$) is a little higher than the Agent-guided protocol ($M_p = 0.73, SD_p = 0.06$), and a t-test shows difference is not statistically different ($t = 0.6, p > 0.05$).

Satisfaction: Human teammates have the highest satisfaction with the agent when using the Agent-guided protocol ($M_p = 3.86, SD_p = 0.8$); ANOVA shows that the difference is not statistically significant, $F = 1.3, p > 0.05$.

Agent Selection and Guidance: We analyzed the preference of human teammates for the allocator role and the level of agent guidance. We found that human teammates select the agent as team task allocator a little more frequently,
in the first, second, third, and fourth episodes respectively. Similarly, we find that for the Identify Landmark task type, we found that human teammates follow the allocation suggestion from the agent teammate more often and increasingly more frequently in later episodes. We expect this difference in performance to increase if the teammates interacted for more episodes. As the agent can have higher input and control in both the Human-selected and Agent-guided protocols, we expected higher performance with those protocols than with the Turn-taking and Performance-based protocols. However, we observe that the Performance-based protocol produced higher performance. This is likely because the first two protocols give the human teammate the option to explore, which they choose to do, whereas that option is not available to them in the Performance-based protocol.

Our previous work showed that humans are less satisfied when they are not the task allocators and human teammate feedback mentioned that they did not like having less control and input in decision-making (Abuhaimed and Sen 2022). Results from our current experiments show that Agent-guided protocol produces the highest satisfaction ratings since it gives full control to the human while also allowing the agent to contribute by providing allocation suggestions. This implies that it is possible to increase human satisfaction without compromising team performance.

The analysis of experimental data suggests directions for future work on human-agent team mechanisms and designs. An interesting direction to pursue would be to present agent allocation suggestions as coming from another human. Experiments using such a “deception” will provide insight into how to present effective allocation suggestions that will be accepted by human teammates. We also want to experiment with scenarios that relax the equal task allocation constraint. Such experiments might further differentiate between the performance and satisfaction with these protocols. Whereas we used intellective task types in this paper, we intend to work with other task types to evaluate these protocols in other scenarios.
References
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