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The Impacts of Multi-Agent Quantity, Type and Transparency on Mental Workload, Situation Awareness and Human Out-of-the-Loop

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ABSTRACT

This study aimed to explore a suitable cooperation mode between human and multi-agent systems. We designed a task scenario that simulated humans working with multiple autonomous agents. Two types of agents were adopted and redesigned: an intelligent assistant that helps operators assign unmanned vehicles, and a semi-autonomous dynamic positioning system for vessels. This research conducted two experiments. The first conducted a 2 (multi-agent quantity) × 2 (multi-agent type) within-subjects experiment. The second investigated the effect of multi-agent type and transparency. The subjective mental workload, SA, out-of-the-loop (OOTL) degree, and performance were measured. The results showed that the more the quantity of agents, the higher the cognitive mental workload, the lower the SA, and the more serious the OOTL degree. The more complex the types of autonomous systems are, the higher the mental workload. When humans interact with multiple autonomous systems, the heterogeneous agents reduce SA compared to homogeneous agents. The higher the transparency of the autonomous systems, the lower the mental workload, the higher the SA, the lower the degree of OOTL, and the better the experimental performance.

Keywords: Autonomous system, Multi-agent, Quantity, Type, Transparency, Mental workload, Situation awareness, Human out-of-the-loop

INTRODUCTION

Artificial intelligence's development, more autonomous systems, robots, unmanned aerial vehicles, and unmanned ground vehicles that can adapt and learn, independently determine goals, and allocate resources to perform specific tasks independently are changing human life (Kaber, 2018). These machines are collectively referred to as autonomous systems. Although these autonomous systems can reduce labor demand, expand human capabilities, and improve human security, they will not be able to complete tasks independently in the foreseeable future and need a human to monitor and cooperate with them (Xiong et al., 2022).

In general, humans mainly monitor the agents' work and verify the completion of their tasks. As a result, the mental workload is significantly reduced, and humans have more free time. Sometimes one operator can monitor multiple agents simultaneously, saving limited resources and reducing labor costs for society. However, increasing the number of agents cooperating with people may overload the human mental workload, thus reducing the operational performance level of the human-agent team (Donmez et al., 2010). At the same time, it may also cause mistakes in human information acquisition and analysis and decision-making errors, leading to accident symptoms and accidents (Cummings et al., 2007). Work organization between autonomous systems and humans is essential in the collaboration process. The ideal way is to maximize the agents' autonomy to expand human ability without causing humans mental overload.

In addition, when people cooperate with multiple agents, there are problems related to the types of agents besides the quantities of agents (Mina et al., 2020). In a real-world scenario, people may need to simultaneously monitor agents of the same kind, but they may also monitor different types of agents simultaneously (Donmez et al., 2010). We named agents with the same functions and principles as homogeneous agents and called agents with different functions and principles heterogeneous agents. How to organize work is a problem that needs to be solved for collaboration between humans and multi-agents. It needs to be clear whether there is a significant difference between monitoring multiple homogeneous agents and multiple heterogeneous agents from the perspective of mental workload. What design should be adopted to reduce the mental workload problems encountered in a human multi-agent team? These are essential questions that still need to be thoroughly studied.

The design that considers transparency in a multi-agent team may provide an improved approach to the above problems. As autonomous agents become more and more complex and independent, agents' intentions, behaviors, and reasoning processes behind them, as well as expected results and other aspects of information, become very important. Humans must acquire effective situational awareness of multiple agents, properly calibrate trust for agents and make appropriate decisions, and achieve high performance in a human multi-agent team. Access to this information depends on the design of transparency for the multiple agents. Transparency refers to the visibility of human or agent information processing processes and decision-making processes. The higher the transparency, the higher the visibility (Chen et al., 2018; Kraus et al., 2020). The level of transparency is usually influenced by interface design and the information content (Guznov et al., 2020).

Based on the above definitions, Chen et al. (2018) proposed a situation awareness-based transparency (SAT) model to assess the level of transparency for autonomous agents, guiding the design of autonomous agent transparency. In this model, transparency can be divided into three levels. An autonomous agent with SAT level 1 (SAT 1) transparency provides essential information, such as current operating status, decision goal, and actions taken, to help humans to perceive agents' behavior. An autonomous agent with SAT level 2 (SAT 2) transparency needs to provide the logical reasoning process of its decisions and the constraints considered in action, to help people understand the behavior of autonomous agents. An autonomous agent with SAT level 3 (SAT 3) transparency predicts the future operating status, decision consequence, likelihood of success or failure, and the uncertainty of the above judgments to help people project the future outcome of the current task.

This study puts forward three objectives to explore a suitable cooperation mode between humans and multiple autonomous agents. First, to examine the impact of the multi-agent quantity on human mental workload, situation awareness (SA), and human out-of-the-loop (OOTL) degree. The second is to study the influence of multi-agent type on the above dependent variable. Thirdly, based on the completion of the first two objectives, a new variable, transparency, is introduced to explore ways to improve the cooperation between human and multiple autonomous agents.

METHOD

Participants

In Experiment 1, 12 undergraduates (7 males and 5 females) were recruited as participants. In Experiment 2, 22 undergraduates (17 males and 5 females) were recruited to participate.

Design

Experiment 1 adopted a 2 (multi-agent quantity: 1, 2) × 2 (multi-agent type: homogeneous, heterogeneous) within-subjects design. The condition of quantity 1 means that operators can only switch to the other agent after interacting with one agent and cannot manipulate multiple agents simultaneously. In other words, the operator only works with one agent at a time but can alternately manipulate the other agent. The other agent may be of the same type (homogeneous) or a different type (heterogeneous). The total amount of work in the experiment was controlled and was the same in different experimental conditions. Therefore, in one case, the agent continues to interact with the same type of agent (homogeneous). After finishing one group, the other type of agent is switched to complete a set of tasks. The other case is switching between agents of different types (heterogeneous), switching after completing one trial, which means alternately manipulating agents of different types. The condition of quantity 2 means that the human monitors two agents at a time. Under the homogeneous condition, two agents of the same type are monitored simultaneously. Under the heterogeneous condition, two agents of different types are monitored. In the four experimental conditions, the total amount of work performed was the same, meaning that the total number of tasks performed was the same. The task scenario diagram of Experiment 1 is shown in Figure 1.

Experiment 2 adopted a 2 (multi-agent type: homogeneous, heterogeneous) × 2 (transparency: SAT 1, SAT 2) within-subjects experiment design. The design details of transparency are covered in the next section.

Simulation Environment and Tasks

Two types of autonomous agents are adopted and redesigned to simulate the scenario of human interaction with two types of agents. The two agents have different functions. One is an intelligent assistant that helps operators assign

Figure 1: The illustrative diagram shows monitoring one agent (left) and two agents (right) at a time.

unmanned vehicles, and the other is a semi-autonomous dynamic positioning system for pre-defined path tracking of vessels, forming a multi-agent team with humans. The former is a multi-unmanned vehicle management assistant designed by Bhaskara et al. (2021) to study the autonomy transparency design to improve the accuracy of using automation. The latter is adapted from an automatic change identification tool designed by Rick van der Kleij et al. (2018) for dynamic vessel positioning to study the impact of automatic change identification on situational awareness recovery in the case of an emergency takeover. The interfaces of the two types of agents are shown in Figure 2.

In Experiment 1, in collaboration with the intelligent assistant (agent 1), the operator assigns appropriate unmanned vehicles to the destination to complete the task according to the task's requirements. According to four attributes of the vehicle (including speed, distance to the search area, fuel efficiency, and search steps), the intelligent assistant calculates the score of each unmanned vehicle's ability to complete the current task (including three dimensions: time to the search area, search time and fuel consumption). A weighted score of vehicle capability is then calculated.

Based on the scores, the intelligent assistant recommends two alternative vehicles (plan A and plan B). Although the calculations of the assistant are reliable, the recommendations are only sometimes optimal because the operator will obtain some up-to-date information, which may interfere with the recommendations. There were three categories of additional information: 1)

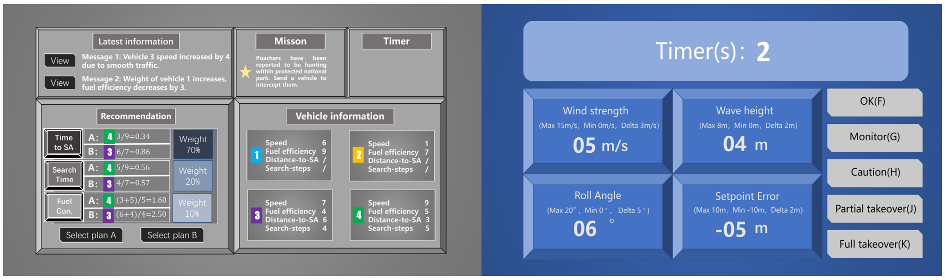

Figure 2: The interface of the intelligent assistant for assigning unmanned vehicles (left) and the interface of the semi-autonomous dynamic positioning system for vessels (right).

information that had no effect on recommendations; 2) information that affected the score of the recommended vehicle but had no effect on the ranking of the scores; 3) information that had an impact on the score of the recommended vehicle and the ranking. The operator needs to make decisions based on the recommendation of the assistant and the latest information.

On the other hand, the operator monitors the job of Agent 2 and ensures the vessel's navigation. When the system is abnormal, the operator can timely intervene appropriately and take over the agent's work if necessary. There are four parameters in the system. The operator's feedback rules are as follows: 1) Four parameters are normal, the operator will give the feedback "OK"; 2) The change amount of 1–2 parameters are abnormal, feedback "Monitor" ; 3) One parameter exceeds the threshold, or the change of 3–4 parameters is abnormal, feedback is "Caution"; 4) One parameter exceeds the threshold and some parameters change abnormal, feedback is "Partial takeover"; 5) Two or more parameters exceed the threshold, feedback "Full takeover".

In Experiment 2, the task was similar to Experiment 1, with some differences in the transparency design. For Agent 1, in the low transparency condition (SAT 1), the "Recommendation" information will only show the recommendation priority without the calculation process. In the condition of high transparency (SAT 2), the "Recommended" indicates the recommendation and shows the reasoning process, namely the calculation of two score items. Participants were shown the formulas for the two points in both SAT 1 and 2 conditions. The difference between the two levels of the transparency interface is shown in Figure 3.

For Agent 2, the system prompts only the abnormal value in SAT 1 condition. In the SAT 2 condition, the agent further analyzes values to assist in diagnosis and displays them on the interface. The interfaces of the two transparency designs are shown in Figure 4.

Measures

The mental workload was measured by the NASA-TLX Scale. Mental requirements, physical requirements, time requirements, operational performance, effort degree, and frustration degree were assessed. Situation awareness was measured by the Situational Awareness Rating Technique (SART) questionnaire, which includes ten questions. Situation awareness was measured

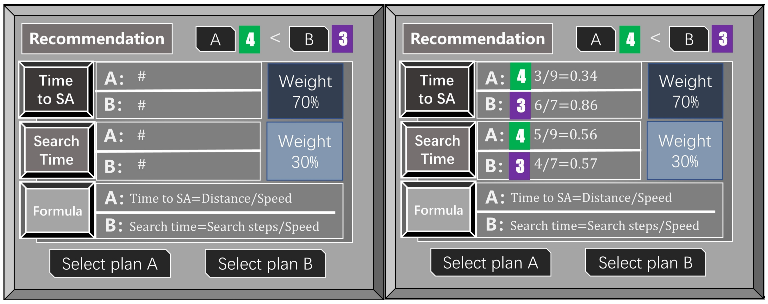

Figure 3: The Recommendation part of the two transparency designs for agent 1.

Figure 4: The interfaces of the two transparency designs for agent 2.

from three dimensions: attention demand, attention supply, and understanding of the situation (Endsley et al., 1998). OOTL degree was measured by the OOTL self-rating scale proposed by Jamieson & Skraaning (2020). The scale consists of four questions to investigate the problems that operators encounter when working with agents in the following aspects: (a) keeping track of the program execution, (b) finding the components needed to run the program, (c) knowing the impact of the program steps, and (d) knowing whether the program introduces certain deviations. In addition, experiment 2 also analyzed performance measured by the accuracy rate.

Procedure

The participants first practiced the tasks and got the correct rate feedback. After the practice, the subjects completed the formal experiment. A total of eight unmanned vehicle assignment tasks and eight vessel dynamic positioning tasks were included in each experimental condition. After the tasks of each condition, participants completed NASA-TLX, SART and OOTL questionnaires. The participants filled in the questionnaires four times, corresponding to four experimental conditions.

RESULTS

The dependent variables passed the tests of normality and homogeneity of variance. ANOVA was used to analyze the influence of independent variables. Bonferroni adjustment was used for post-hoc analysis. The effect size was measured with partial eta-squared (η_p^2).

Experiment 1

The Means and standard deviations of the dependent variables are summarized in Table 1. The ANOVA results of mental workload (Table 2) indicated significant main effects of multi-agent quantity ($F(1, 11) = 51.58$, $p < 0.001$, $\eta_p^2 = 0.824$) and type ($F(1, 11) = 6.20$, $p = 0.03$, $\eta_p^2 = 0.360$). The mental workload of monitoring two agents working together ($M_{quantity = 2} = 48.33$) is higher than monitoring only one agent at a time ($M_{quantity = 1} = 39.79$), even though the total number of tasks is the same. The mental workload of monitoring heterogeneous agents ($M_{heterogeneous} = 45.42$) is higher than monitoring homogeneous agents ($M_{homogeneous} = 42.71$).

Table 1. Means and standard deviations of the measures.

Measures	Quantity 1		Quantity 2	
	Homogeneous Mean (SD)	**Heterogeneous Mean (SD)**	**Homogeneous Mean (SD)**	**Heterogeneous Mean (SD)**
NASA-TLX	38.58 (7.80)	41.00 (8.48)	46.83 (10.18)	49.83 (4.09)
SART	24.67 (7.61)	25.25 (6.70)	18.17 (5.20)	15.08 (6.64)
OOTL	12.33 (7.38)	13.00 (5.33)	15.92 (5.60)	15.92 (5.53)

Table 2. Results of ANOVA for NASA-TLX.

	F	df_1	df_2	p	η_p^2
Quantity	51.58	1	11	< 0.001	0.824
Type	6.20	1	11	0.030	0.360
Quantity × Type	0.04	1	11	0.848	0.003

The ANOVA results of SART (Table 3) indicated a significant interaction effect between multi-agent quantity and type ($F(1,11) = 5.64$, $p = 0.037$, $\eta_p^2 = 0.339$). The post-hoc results indicated that when collaboration with two agents at a time, heterogeneous agents resulted in a more significant loss of situational awareness than homogeneous agents ($M_{homogeneous} = 18.17$, $M_{heterogeneous} = 15.08$, $t(11) = 2.564$, $p = 0.026$). When operators monitored only one agent at a time, situational awareness had no significant difference between a heterogeneous agent and a homogeneous agent. Meanwhile, the main effect of quantity was significant ($M_{quantity = 1} = 24.96$, $M_{quantity = 2} = 16.63$, $F(1, 11) = 18.31$, $p = 0.001$, $\eta_p^2 = 0.625$), indicating a significant loss of situation awareness when operators monitored two agents at a time.

The ANOVA results of OOTL degree (Table 4) indicated significant main effects of multi-agent quantity ($F(1, 11) = 34.22$, $p < 0.001$, $\eta_p^2 = 0.757$). The OOTL degree of monitoring two agents working together ($M_{quantity = 2} = 15.92$) is higher than monitoring only one agent at a time ($M_{quantity = 1} = 12.67$), even though the total number of tasks is the same.

Table 3. Results of ANOVA for SART.

	F	df_1	df_2	p	η_p^2
Quantity	18.31	1	11	0.001	0.625
Type	2.24	1	11	0.163	0.169
Quantity × Type	5.64	1	11	0.037	0.339

Table 4. Results of ANOVA for OOTL.

	F	df_1	df_2	p	η_p^2
Quantity	34.22	1	11	< 0.001	0.757
Type	0.693	1	11	0.423	0.059
Quantity × Type	0.141	1	11	0.715	0.013

Experiment 2

The Means and standard deviations of the dependent variables are summarized in Table 5. The ANOVA results of the four measures indicated significant main effects of agent transparency (Table 6–9). Working with multiple agents with high transparency will reduce mental workload, improve situational awareness, reduce OOTL, and improve performance.

Table 5. Means and standard deviations of the measures.

Measures	SAT 1		SAT 2	
	Homogeneous Mean (SD)	Heterogeneous Mean (SD)	Homogeneous Mean (SD)	Heterogeneous Mean (SD)
NASA-TLX	40.64 (8.28)	43.50 (7.48)	35.23 (7.86)	37.64 (7.46)
SART	18.45 (8.59)	16.50 (7.34)	23.23 (6.75)	21.91 (7.38)
OOTL	13.55 (4.83)	14.09 (5.11)	11.91 (5.51)	11.68 (4.86)
Performance	0.75 (0.14)	0.74 (0.15)	0.83 (0.09)	0.81 (0.11)

Table 6. Results of ANOVA for NASA-TLX.

	F	df_1	df_2	p	η_p^2
Transparency	17.82	1	21	< 0.001	0.459
Type	3.12	1	21	0.092	0.129
Transparency × Type	0.05	1	21	0.829	0.002

Table 7. Results of ANOVA for SART.

	F	df_1	df_2	p	η_p^2
Transparency	18.01	1	21	< 0.001	0.462
Type	1.92	1	21	0.180	0.084
Transparency × Type	0.07	1	21	0.800	0.003

Table 8. Results of ANOVA for OOTL.

	F	df_1	df_2	p	η_p^2
Transparency	7.45	1	21	0.013	0.262
Type	0.06	1	21	0.804	0.003
Transparency × Type	0.20	1	21	0.660	0.009

Table 9. Results of ANOVA for performance.

	F	df_1	df_2	p	η_p^2
Transparency	13.65	1	21	0.001	0.394
Type	0.59	1	21	0.451	0.027
Transparency × Type	0.03	1	21	0.862	0.001

DISCUSSION

Goodrich et al. (2005) raised that different mental models are required for different types of agents. Arrington & Logan (2004) proposed that in the cooperation between humans and multi-tasks, people must choose when to switch from one task to another, which will also affect people's mental workload. Wong & Seet (2017) also raised that the competition for attention resources caused by multiple agents affects mental workload. Monitoring heterogeneous agents have two different mental models compared to homogeneous agents. Monitoring multiple agents simultaneously increases the attention resource competition load and task switching load compared with monitoring one agent. Therefore, this paper explored the effects of the quantity and types of agents on the dependent variables such as mental workload, situation awareness, OOTL degree, and performance when people interact with multiple agents.

The results showed that the number of agents would significantly impact mental workload, which is the consensus of previous studies. It shows that cooperation with multiple agents will bring problems with attention allocation and increase the mental workload. According to the SART and OOTL scores, the increase in the number of agents significantly reduced the situation awareness and increased the degree of OOTL. Secondly, the agents' types also significantly impact mental workload, an influential factor that has not been studied before. It is worth noting that, from the perspective of mental workload, the influences of type and quantity are not the same (by comparing the effect size). When the number of agents monitored at a time is only one, the type has no effect on situation awareness. Only when the number of agents increases to two the situational awareness will be affected by type. However, there was no significant relationship between the type of agent and OOTL.

In the second experiment, transparency design was introduced to improve human and multiple agents interaction. Some studies proposed that improving transparency will bring new information and enhance people's situational awareness (Endsley, 2017). But some studies revealed that adding information will increase the amount of information needed to display, which may require additional cognitive efforts (Chen et al., 2018). The results of previous experiments showed no consistent conclusion on whether enhancing transparency can affect performance. After reviewing some empirical studies on transparency, Rajabiyazdi & Jamieson (2020) conclude that the correlation between transparency and performance is still uncertain. In this paper, we found that transparency can reduce mental workload, improve situation awareness, reduce OOTL degree, and improve team performance. From an application perspective, a higher level of transparency would be a cost-effective option for improving agent teams. According to the SAT model, from level 1 to level 2 only requires displaying the reason for the decision, and from level 2 to level 3 requires predicting the future outcome. Transparency design is more actionable than purely thinking about improving the intelligence and autonomy of agents.

CONCLUSION

This study has significant theoretical and applied value. It can improve the existing theories of work organization between autonomous systems and humans, provide a new perspective from the perspective of mental workload, and improve the current research on multiple agent transparency. In practical application, it can help enterprises and individuals decide what work organization mode to adopt in the human multi-agent team. It also has essential reference value in the design of multiple autonomous systems. Priority can be given to the trade-off on the quantity of agents. When it is inevitable to make humans interact with multiple agents, the transparency of the autonomous systems can be improved to increase explainability, reduce mental workload and enhance task performance.

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