Operator Workload and Task Allocation in m:N Operational Architectures of Uncrewed Aerial Systems

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Uncrewed aerial systems (UAS) show promise in urban air transport, package delivery, and emergency services. UAS efficiency can be significantly improved by having fewer operators (m) manage a greater number of vehicles (N), or the m:N architecture of operation. The current study investigates how workload affects operators' task-allocation decision-making and potential effects of two crucial human factors: trust and self-confidence. In the context of a simulated UAS package-delivery task, 10 participants with expertise in UAS operation were recruited. Each participant reported their preferred task-allocation strategy for a set of five subtasks while watching two sets of videos with different workload levels. Perceived workload, trust, and self-confidence were also measured after each video session. Overall, participants indicated a preference for automation for most of the subtasks under the delivery mission. Trust, rather than workload and self-confidence, played a significant role in experts' decisions of task-allocation and assignment methods. Higher trust led to higher preference for automation.

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I. Introduction

In recent years, there has been an emerging discussion on Advanced Air Mobility (AAM) due to technical advances and traffic concerns [1]. The AAM concept includes aerial vehicles of any kind, such as commercial aircraft, urban air taxis, and small unmanned aerial vehicles (UAVs). Also, AAM has a wide range of potential applications, such as package delivery, passenger carriage, and emergency services [2]. One important concept within the AAM framework is Remote Vehicle Operations (RVO), which allows for the physical separation between the vehicle operator and the aerial vehicle [3]. RVO enables a team of operators to manage a larger number of vehicles simultaneously (i.e., the m:N operational architecture), thus increasing system efficiency and reducing the demand for trained pilots [4, 5]. However, lower human-to-aircraft ratios require a higher level of support from automated systems and better collaboration between humans and automation [3, 6]. Thus, it is important to investigate the crucial human factors that might affect operator decision making and preferences.

Mental workload has been an important human factors concept. It is often described as the pool of cognitive resources employed to perform tasks [7]. One of the most widely employed subjective measures for workload is the NASA Task Load Index (TLX) [8]. With technology developments in the ground and air transportation industry, there is an increasing level of automation in vehicle operation. However, automation does not always lead to reduced mental workload. Poor automation design can lead to increased workload if the operator is unfamiliar with the tasks when there is an automation failure [9].

With the increasing integration of automation in uncrewed aerial systems (UAS), strategically assigning or shifting authority from human operators to autonomous agents is a viable approach to achieving decreased workload and increased system efficiency [5, 10]. Parasuraman and colleagues [10] studied performance in a multi-task flight simulation in which participants were instructed to monitor engine status while performing tracking and fuel management tasks simultaneously. Throughout the experiment sessions, all engine-status monitoring tasks were automated for the control group, whereas the adaptive groups performed the tasks manually for 10 minutes in the middle of the experiment blocks. Following the manual trial, the adaptive groups identified significantly more automation errors compared to the control group [10]. These results showed that using adaptive task-allocation strategies between automation and human operators can significantly improve task outcomes.

Trust is another major component in the decision-making process of human operators in automated systems [11, 13]. McNeese and colleagues [12] employed the Wizard of Oz technique to simulate an automated agent that acted as the participants' collaborator in a navigation and photography task. The level of trust and participants' mission performance were measured using a trust questionnaire and a composite score of time and number of targeted photos, respectively. Through a multivariate cluster analysis, McNeese and colleagues [12] found that higher levels of trust were associated with better team performance, whereas lower levels of trust were associated with poorer team performance.

The operator's self-confidence in performing a task can also interact with trust and impact decision-making [13]. More specifically, operators are more likely to perform the tasks manually if they have high self-confidence yet low trust in automation [14]. Riley [15] reaffirmed this result by comparing task-allocation decisions made by students in two tasks: categorizing a character as either a letter or number and correcting disturbances from a target location. Participants were told they were given an automated tool to assist with the first task. The group of participants who reported a high level of self-confidence employed the automation tool less frequently, compared to the group with a low level of self-confidence [15].

The current study aims to provide a better understanding of the dynamics between operator perceived workload, trust, and self-confidence within the framework of an m:N operational architecture. The findings indicate that trust is a pivotal factor in shaping experts' preferences for task-allocation and assignment methods. Higher levels of trust were associated with an increased inclination towards using automation for task allocation. By analyzing these essential human factors in a high-fidelity UAS simulation, this study provides valuable insights that can improve UAS safety and operational efficiency by highlighting the significant role of trust in decision-making processes.

II. Method

A. Participants

A total of 10 expert participants were recruited. Experts were defined as those who either have an FAA-certified pilot license for small UAS (Part 107) or have at least 10 hours of experience operating drones. The participants had a mean age of 33.90 years old (*SD* = 9.24). Nine of them self-identified as male and one as female. On average, the experts spent approximately 270.5 hours operating drones (*SD* = 290.27), with the minimum being 10 hours and the maximum being 800 hours. All participants were adults with normal or corrected-to-normal hearing and vision. They were recruited through emails, community posters, flyers, word of mouth, and social media sites. Each participant was paid $50 in the form of an Amazon gift card for their participation, along with a parking validation when applicable. This study was approved by the Institutional Review Board at Rice University.

B. Apparatus and Stimuli

The experiment setup is shown in Figure 1. The simulated map and environment were created based on a suburban area in Waco, Texas. The experiment stimuli were set up in AirSim (a simulation environment) [16], QGroundControl (QGC; a UAV route planning software) [17], and Qualtrics (an online survey website) [18].

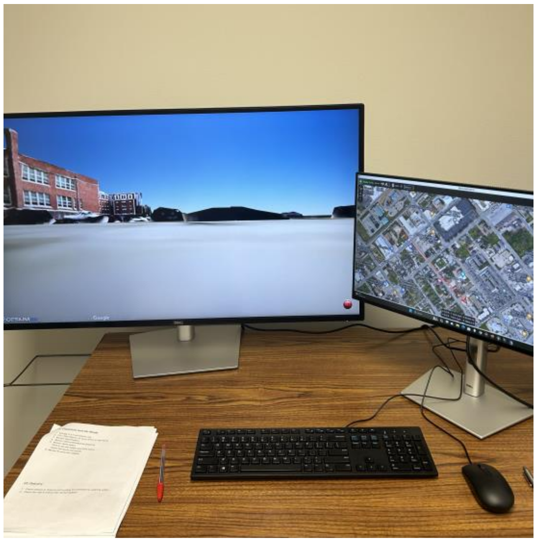

Fig. 1 Experiment set up: the simulated camera view of the drone (left) and the QGC interface (right)

In this experiment, we employed a within-subject design with the number of UAVs (i.e., drones) of 6 vs. 12 being the independent variable. In the pre-experiment survey, participants were asked about their age and whether they have normal or corrected-to-normal vision and hearing. A training session was employed to familiarize participants with the software and delivery tasks.

Two sets of videos of drones performing delivery tasks in a suburban environment were presented during the main experiment. One set of videos included the operating screen of 6 drones (including the operating panel and the simulated recordings of drones delivering packages following a designated route). The other set of videos had the same display but with 12 drones. The order of which set of videos was presented first was counterbalanced. Each experimental video set included five videos, each depicting a subtask: Pre-Departure Planning, Route Planning, Departure and On-Route, Delivery, and Return. The crucial steps included in each subtask are shown in Table 1. After each video, they were directed to answer questions regarding task-allocation preferences, workload, self-confidence, and trust in automation on a separate monitor. For task-allocation preferences, the participants were asked to indicate how they want the tasks to be performed or assigned on a sliding scale from 0 (“Manual Only”) to 100 (“Automation Only”) and explain their reasoning.

Right after answering these questions, perceived workload and trust in automation were measured using the NASA-TLX [8] and an adapted version of the Trust in Automation Questionnaire [19]. Additionally, self-confidence in performing the respective subtask was measured via a 7-point Likert scale from strongly disagree to strongly agree. Following these questions, a contingency scenario was introduced, and participants were then queried about their responses to the scenario. However, these questions and responses are beyond the scope of this paper and thus not reported. At the end of the study, participants answered questions on their ethnicity, gender, video game experiences, UAS experiences, and pilot certifications.

Table 1 Subtask details

Subtask	Crucial Steps
Pre-Departure Planning	Setting up vehicle speed, altitude, and geofence
Route Planning	Finding delivery address on the map, set up waypoints, and set up loitering
Departure and On-Route	Selecting multi-vehicle view, start mission, confirm mission start, and monitor battery status
Delivery	Checking surrounding environment for loitering safety
Return	Checking GPS status, battery status, and landing environment

III. Results

A. Quantitative Results

1. Effects of number of drones

To check whether the number of drones affected participants’ perceived workload, preferences on who should perform a subtask, as well as who should assign the subtask, separate linear mixed regression analyses were conducted with the number of drones (6 or 12) as the predictor and subtask as random factor on each of these variables. Although the mean values showed that the 12-drone condition had higher perceived workload and more preferences on the automation to perform the subtasks and be in charge of assigning the subtasks, none of these effects were statistically significant. Specifically, there was no significant difference in perceived workload between the 6-drone condition (*M* = 8.81, *SD* = 3.56) and the 12-drone condition (*M* = 10.26, *SD* = 4.09), $t(98) = 1.90$, $p = .061$. The number of drones did not significantly predict answers to the question "who [automation or yourself] would you choose to perform this task" between the 6-drone condition (*M* = 71.68, *SD* = 33.61) and the 12-drone condition (*M* = 77.24, *SD* = 29.97), $t(94) = 0.88$, $p = .380$. Additionally, there was no significant difference on answers to the question "If given an automated tool, would you choose to assign this subtask manually (by yourself) or automatically (by the automation)?" between the 6-drone condition (*M* = 68.88, *SD* = 34.98) and the 12-drone condition (*M* = 74.90, *SD* = 30.53), $t(94) = 0.99$, $p = .326$. As a result, we use perceived workload as measured by NASA-TLX in the following analyses.

2. Effects of trust, self-confidence, and perceived workload

Multiple regressions were conducted on participants' preference on who should *perform* the tasks (task allocation) using trust, self-confidence, and perceived workload as predictors. The results are shown in Table 2. The overall model was significant for the subtask "Departure and On-Route" and "Return." Out of the three predictors, trust significantly predicted task-allocation preferences for the subtasks of "Departure and On-Route," "Delivery," and "Return". For these subtasks, higher trust in automation led to higher preference to allocate the tasks to the automation.

Separate regressions were conducted on participants' preference on who should *assign* the tasks (task assignment) using trust, self-confidence, and workload as predictors. The results are shown in Table 3. None of the regression models were significant, indicating that task assignment might not be significantly affected by the three predictors (trust, self-confidence, and workload). However, trust significantly predicted task assignment preference in the subtask "Return," with higher trust in automation leading to higher preference for the automation to assign this task.

Table 2 Multiple regression results on allocation preference

Subtask	$F(3, 16)$	p	R^2	Trust		Self-Confidence		Perceived Workload	
				$t(16)$	p	$t(16)$	p	$t(16)$	p
Pre-Departure Planning	1.46	.264	.07	0.87	.397	0.69	.503	1.49	.157
Route Planning	1.64	.220	.09	0.93	.369	1.75	.100	0.30	.765
Departure and On-Route	6.08	.006	.45*	4.16**	.001	0.77	.455	0.03	.979
Delivery	2.72	.079	.21	2.27*	.038	0.90	.381	0.06	.954
Return	3.72	.033	.30*	2.83*	.012	1.05	.310	0.95	.357

Note. * indicates $p < .05$, ** indicates $p < .001$.

Table 3 Multiple regression results on assignment preference

Subtask	$F(3, 16)$	p	R^2	Trust		Self-Confidence		Perceived Workload	
				$t(16)$	p	$t(16)$	p	$t(16)$	p
Pre-Departure Planning	2.56	.092	.20	1.47	.162	1.64	.121	1.93	.071
Route Planning	1.69	.209	.10	0.70	.494	1.26	.228	1.58	.135
Departure and On-Route	1.12	.369	.02	1.47	.160	0.24	.812	1.08	.298
Delivery	1.79	.190	.11	0.78	.450	0.08	.935	2.02	.061
Return	2.22	.125	.16	2.56*	.021	0.16	.878	0.15	.880

Note. * indicates $p < .05$.

3. Task-allocation preferences

Given that participants' task allocation preferences were reported on a scale of 0 (0 = manual only; 50 = no preference; 100 = automation only), independent *t*-tests (two-tailed) were conducted to examine whether participants' expressed preferences were significantly different from "no preference" (see Table 4). Participants' task-allocation preferences were significantly different from 50 (no preference) for subtasks "Pre-Departure Planning," "Route Planning," "Departure and On-Route," and "Return," but not for subtask "Delivery." These results showed that participants had significant preferences for automation to perform all of these subtasks except "Delivery."

Table 4 Independent *t*-tests results on allocation/assignment preferences (compared to 50)

Subtask	Allocation					Assignment				
	M	*SD*	*t*(19)	*p*	*d*	*M*	*SD*	*t*(19)	*p*	*d*
Pre-Departure Planning	70.05	37.76	2.37*	.028	0.53	51.50	37.34	0.18	.859	0.04
Route Planning	68.50	35.06	2.36*	.029	0.53	62.00	38.75	1.39	.182	0.31
Departure and On-Route	84.05	24.52	6.21**	<.001	1.39	79.65	29.35	4.52**	<.001	1.01
Delivery	66.15	37.41	1.93	.069	0.43	76.75	26.90	4.45**	<.001	0.99
Return	83.55	17.33	8.66**	<.001	1.94	89.55	13.00	13.60**	<.001	3.04

Note. * indicates $p < .05$; ** indicates $p < .001$.

Similar analyses were conducted on participants' task-assignment preferences. Their task-assignment preferences were significantly different from "no preference" for the subtasks "Departure and On-Route," "Delivery," and "Return," but not for subtasks "Pre-Departure Planning" and "Route Planning" (see Table 4). These results showed that participants had a significant preference for automation to assign these three subtasks except "Pre-Departure Planning" and "Route Planning."

B. Qualitative Results

Participants were asked about the reasoning of their indicated preferences. This subsection summarizes the major themes that arose from their comments.

The experts preferred automation mainly because the tasks were time-consuming, non-critical, and repetitive. They also believed that automation was more precise and efficient. Some of the related comments included:

The process of checking the battery levels is time-consuming and irrelevant.

It's quicker.

This can save time.

Automation tool would be more precise.

Drone obstacle avoidance technology currently exist so this is a very easy task to be completed via automation.

Too many drones for one person to handle.

However, some experts preferred manual operation because they preferred human supervision, and they believed that a human operator would be more knowledgeable and secure. Some of the related comments included:

The operator can choose to visually confirm the geofence.

Manual Planning needs to be done to maximize safety.

It would make more sense for a person to decide what steps of the process would be easy to automate or not.

Manually selecting manual or automatic depending on the complexity seems to make more sense.

The video monitoring should be monitored by a manual operator to ensure mission safety and mission completion.

IV. Discussion

The current study separated a UAS package delivery mission into five subtasks and investigated the effects of workload, trust in automation, and self-confidence on each subtask. The primary goal was to investigate whether these factors affect experts' preferences on task allocation and task assignment between the human operator and the automation. We also implemented two levels of workload with 6 drones being operated in the low-workload condition and 12 drones in the high-workload condition. However, the results indicated that the number of drones did not significantly predict perceived workload (measured by NASA-TLX), nor participants' preferences on either how they wanted the task to be performed or assigned. There were a few possible explanations for there not being a difference between the two conditions. The first possibility was that participants might not get an accurate perception of the workload in each condition through watching the videos. Another potential explanation was that the 6-drone mission might already be overwhelming for participants, so increasing the number of drones to 12 only increased the workload marginally. This was evident in some of the comments made by the participants. Some mentioned that "if the number of drones is more than four, I have to split my vision between checking battery and cameras on the right side;" and "the number of drones only changed my decision a little bit because 6 is already a lot. I would say four is the cutoff." Alternatively, the results could indicate that workload is not a crucial factor in the experts' decisions on how the tasks should be performed or assigned. To further investigate these results, a larger sample size should be acquired to ensure the power of the analysis in future studies.

Trust was a significant predictor of participants' task allocation preference for subtasks Departure and On Route, Delivery, and Return, as well as task assignment preference for subtask Return. This is consistent with previous literature that lower trust in automation leads to less automation use [14, 20]. The difference in task-allocation preferences between subtasks indicates that participants emphasized mission responsibility more for the later subtasks, compared to early subtasks including "Pre-Departure Planning" and "Route Planning." Because the last three subtasks were more mission-critical and time-sensitive, trust in automation had a greater impact on whether participants chose to let automation perform the tasks. In addition, "Return" might be considered a repetition of the steps involved in previous subtasks, such as checking battery, checking camera, and flying the same route. Thus, participants might be willing to give automation more authority, leading to trust being a significant predictor of task assignment preferences for "Return."

Participants' preferences for task allocation in the initial subtasks, "Pre-Departure Planning" and "Route Planning" remained consistently neutral regardless of their levels of trust, self-confidence, or perceived workload. This lack of preference could be attributed to the fact that these tasks are completed before drone takeoff, involving minimal risk and allowing for greater tolerance of errors. Consequently, participants showed no strong inclination towards either automated or manual operation for these steps.

Additionally, our results suggested that workload was not a significant predictor of task allocation or assignment in any of the subtasks. This finding was contradictory to past literature as past research suggested that high workload led to more handoffs [5] and higher preference for the automated system to complete more tasks [21]. This could partially be due to the manipulation of drone number on workload being unsuccessful. Future studies should investigate this relationship with a bigger difference between the number of drones across conditions. Self-confidence was also not significant in predicting task allocation/assignment preferences. This was contradictory to past studies that suggested low self-confidence led to more involvement of automation [15,20]. This result could be due to the smaller sample size in the current study. A post-hoc power analysis showed that the power of the multiple regression models ranged from 0.11 to 0.67. Future studies should employ a larger sample size to achieve higher power.

V. Conclusion

Overall, expert participants showed a clear preference for using automation. They expressed greater preferences for the automation to perform a subtask for four out of the five subtasks and greater preferences for the automation to assign a task for three out of the five subtasks in this study. Contrary to our prediction, the number of drones did not significantly predict perceived workload. However, higher trust in automation led to significantly higher automation preference in the subtasks "Departure and On-Route," "Delivery," and "Return." In the comments made by the experts, those who preferred automation thought automation is more efficient, precise, better at repetitive tasks, and capable of handling higher number drones compared to humans; those who preferred manual operation commented that humans are more knowledgeable about the mission, can make safer and better judgements based on the complexity of the tasks, and can see the surrounding environment better.

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