Performance, Workload, and Situation Awareness in Manual and Automation-Aided Rendezvous and Docking

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BACKGROUND: Manual rendezvous and docking (RVD) is challenging for the astronauts, and automation is used to aid this operation. However, the automation mode in the final approaching stance of RVD is quite different. This paper is aimed at investigating the effect of automation on performance, workload and situation awareness (SA) among novice and expert operators in RVD.

METHODS: A two-factor mixed experimental design was adopted. There were 15 novices and 12 experts who participated in the experiment. All subjects were required to finish six tasks of two automation levels: manual RVD and automation-aided RVD. The Performance was assessed by docking result and control process. Workload and SA were measured by NASA Task Load Index and Situation Awareness Rating Techniques (SART). Repeat measures ANOVA and the simple effect test were used to analyze the effect of automation, skill level, and the interaction between them on performance, workload, and SA of operators.

RESULTS: Novices exhibited performances inferior to experts, but the skills gap was attenuated as automation was introduced. Moreover, automation can enhance performance, reduce workload, and enhance SA for novices, but potentially deteriorate task performance and SA for the experienced. Mediation analysis results indicated automation was a significant predictor of workload and SA, $b = -0.576$ and $b = 0.503$, and workload and SA were significant predictors of docking result, $b = -0.590$ and $b = 0.348$.

CONCLUSION: Automation can be detrimental to various elements of the functioning of highly experienced operators. Moreover, automation affects docking result by affecting workload and SA.

KEYWORDS: manual rendezvous and docking, automation, skill, performance, workload, situation awareness.

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Rendezvous and docking (RVD) is essential in manned spaceflight missions and has been widely used while in orbit to assemble large units, replenish supplies, and exchange the crew.[29] Space RVD is considered as a highly challenging and dynamic process, in which complex cognitive processes are required to handle the large amount of continually changing information in a three-dimensional environment. There are two control modes for RVD, manual control and automatic. These two modes typically serve as mutual backup during spaceflight. However, the preference of control modes varies according to the nationality of the space program. Russia uses mainly automatic control, and manual RVD serves as backup; whereas in the United States of America manual RVD is mainly used, with automatic mode as supplementary. In China, final approach and docking operation is usually performed in a way that the astronaut performs translational maneuvers; the automatic system performs rotational maneuvers. Theoretically, automatic RVD can be regarded as automation where the cognitive and manipulative task of navigation is no longer performed by the astronaut alone but is shared with a machine. Although technical benefits have been suggested,[26]

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questions still remain as to whether the automatic system in RVD can enhance performance and situation awareness (SA) and reduce mental workload.[21] Answering these questions can expand our knowledge on evaluation of automation from a human factors perspective.

Automation is capable of carrying out various functions that once were performed by humans and it has also been extended to functions that humans do not wish to perform or cannot perform as accurately or reliably as machines. Due to benefits such as increased safety, efficiency, and capacity that automation can provide, automation has been intensively applied in diverse domains such as aviation, manufacturing, medicine, and transportation. The advent of automation technologies has stimulated much research on automation and human performance.[12] A major conclusion is that automation fundamentally changes the nature of the task demand and responsibilities of human operators, with the role of operators shifting from manual to supervisory control.[24] However, in different empirical studies of vehicle and nuclear power plant operation automation appears to produce both beneficial and harmful effects on human performance.[25] The benefit is to reduce the dependence on the limited-processing-capacity of human operators. Yet, poor automation design can lead to a reverse effect, such as increased workload and training, reduced SA, and accidents.[17] For man-machine systems, the lack of proper feedback to the operator can lead to human errors when the situation exceeds the capabilities of the automated equipment.

The effect of automation on mental workload and SA of operators is also a major concern in human-automation interaction.[20] Even though there is no consensus regarding its definition, mental workload can be seen in terms of mental resources expended. It gives an indication about the amount of effort invested in a task as well as users' involvement level. Although it is difficult to argue for a direct causal link between workload and performance, a substantial body of research supports a relationship between mental workload and performance.[13] Automation aims to reduce the workload of operators. However, automation actually converts manual tasks into monitoring tasks with humans acting as supervisors. This might impose considerable mental workload on operators even though physical workload is reduced.[17] In this case, the use of an automated system would only lead to a workload-shift instead of a workload reduction. Studies have also shown that some automation may problematically increase workload when demand is high if the automation is not properly designed.[16,24] Examples from aviation show that sometimes the operation of automation is so complex that it even leads to an overall increase in workload.[2] SA is an operator's dynamic understanding of "what is going on,"[20,23] which has been described as "the detection of the elements in the environment within a volume of space and time, the comprehension of their meaning, and the projection of their status in the near future".[5] The situation in human-machine systems changes dynamically with time, thus it is widely accepted that proper SA is required for successful and safe performance in dynamic and complex tasks such as piloting an aircraft and air traffic control operations.[6] Impaired or inadequate SA has been identified as one of the primary factors in accidents attributed to human error.[10] When transferred to the RVD task, SA might comprise how well operators perceive and understand all relevant cues needed to assess the current status of the RVD task, and how well appropriate predictions can be derived about the further dynamic changes of the operation.

A related issue in automation is the out-of-the-loop performance problem.[4] Operators might have diminished ability to perform tasks manually due to a reduced awareness of the state and processes of the system when confronted with an unexpected situation. There are three reasons for an out-of-the-loop performance problem: vigilance problems when monitoring the automated system, passive information processing, and the lack of proper feedback.[4] However, automation can also increase SA.[4] It is generally argued that automation should support SA by offering better and more integrated information to the operators. Given this information, they will be better able to distribute their attention, and SA will be improved by a significant reduction of workload. Thus, effects of automated RVD on workload and SA need to be carefully considered.

Moreover, researchers have also found that automation may have different influences on operators with different skill levels. For example, Hancock found that in a flight simulation, the use of experienced professionals showed fewer significant changes in human-machine system performance under the automation-aided situation than reported previously in studies using volunteer undergraduates, which indicated that automaticity gained by practice and automation can be overlapping.[7] Research revealed that certain tasks are more likely to develop automaticity from repeated practice, thus making plentiful resources available for other tasks.[1] It is assumed that both novices and experts essentially satisfy the criteria for automaticity when faced with automation, thus the novice-expert difference may be lessened.

The purpose of the present study is to investigate the influence of automation in RVD on operators from a human factors perspective. Moreover, we expand upon previous research by investigating whether there was a joint influence of automation and skill level, and what the presence of an interaction implies. The results may provide an evaluation of automatic systems from a human factor perspective and present advice for the design of automatic system and training methods.

METHODS

Subjects

There were 27 male right-handed subjects from the China Astronaut Research and Training Center, all with bachelors' degrees, who participated in the experiment. All subjects were in good physical condition and mental state, without taking drugs, including tobacco, and using alcohol both habitually as well as within the testing. They were divided into novice group (15 subjects) and expert group (12 subjects) based on their RVD experience. The novice group were science and engineering graduate students with no RVD operational experience (mean age = 23.2, SD = 0.86, range from 22 to 25), while the expert group included 4 astronauts, 5 reserve astronauts, and 3 astronaut trainers, who had at least 300 class hours of manual RVD operations experience (mean age = 37.2, SD = 7.03, range from 31 to 48). No novice subjects were familiar with manual RVD procedures, and it was assumed that they were all on the same level of procedural knowledge before the experiment. All experts were trained under manual conditions and had no experience of automation-aided RVD task before the experiment. Subjects filled out informed consent before the experiment and were paid for participation after the experiment. The experimental program was reviewed and approved by the Institutional Review Board (IRB) of University of Science and Technology Beijing.

Materials

A two-factor mixed design was used in the experiment. Level of automation constituted the within-subjects factor and consisted of two levels: manual RVD, and automation-aided RVD. Presentation order was randomized to counterbalance practice effects. RVD operation skill level was the between-subjects factor and consisted of two levels: novices and experts.

Manual RVD is a challenging space task for astronauts. They are required to maneuver an active chaser spacecraft into the vicinity of and eventually make contact with a passive vehicle (the target, e.g., the space station). In performing this task, the subjects are required to control the chaser (i.e., Shenzhou spacecraft) to approach the target (i.e., Tiangong space lab) and connect with it. Subjects can use two handles to control the position and orientation of chaser. The left handle is also called the position handle and controls the movement, direction and speed of the chaser. The right handle is also called the orientation handle and controls the orientation of the chaser. When performing manual RVD, operators must correctly represent the relative position of both the vehicle in the 3-D space and adjust the 6 degrees-of-freedom (DOF) motion of the chaser, which imposes high cognitive demands on operators. Therefore, the automatic system was developed to assist astronauts in RVD tasks. The main goal of the automatic system is to minimize the attitude deviation of the spacecraft and the operator manipulated the position handle to coordinate with the orientation handle by the automation to optimize the whole task. The automatic system can perform a soft docking operation, aiming to reduce workload of astronauts by providing support for such a perceptual-cognitive demanding task. Alternatively, the astronaut may perform translational maneuvers, while the automatic system performs rotational maneuvers. Astronauts are still required to interact with autonomous systems and be ready to take over as there is value in keeping humans in the loop to adapt to the changing situation.[21] Referring to the model of Parasuraman et al.,[19] the automatic systems represent a comparatively high degree of automated assistance that supports implementation of actions.

Experiments were conducted using a manual RVD simulator located in the China Astronaut Research and Training Center. Subjects interacted with the interface via a standard computer mouse and two handles. At the beginning of each scenario, the chaser was 120 m from the target (this is generally the point where autopilot terminates and manual control begins in the real RVD task). Subjects were required to observe the target spacecraft image and parameters in the display, estimate the relative position and orientation of the two spacecraft, and make decisions about which handle to operate and how to manipulate it throughout RVD. Unfortunately, we were unable to obtain the data of how the docking operates, how the forces of rotation, attitude, and speed are measured and controlled, etc. due to some permission issues.

Two modes of tasks were included: the manual RVD and the automation-aided RVD. During the manual RVD task, operators were required to utilize a position handle as well as an orientation handle and perform 6 DOF motion of the spacecraft. During the automation-aided RVD scenarios, operators were required to operate a position handle, with automation performing rotational maneuvers of the spacecraft. Subjects were informed that even if the task of monitoring and adjusting angular deviation was highly automated, they were still responsible for supervising the system and reacting to unpredicted emergencies. For example, if there were any orientation deviations that needed to be manipulated, it was the operator's responsibility to assume control of the orientation handle. The reason for this is that even though the RVD operational task can be fully automated, it requires a backup manual control capability so that astronauts can take over when the automated system or a critical subcomponent of the spacecraft fails.[25] Humans are likely to remain vital to system performance in open loop systems that are commonly found in control environments.[21] Once the operator intervenes, the operation mode reverts into manual mode.

To complete RVD successfully, the relative position and orientation of two spacecraft had to meet the strict conditions of position deviation, orientation deviation, and relative velocity the moment they were docking. The goal of operators was to complete RVD in a successful, precise and fuel-efficient manner.

There were three dependent variables in the experiment: performance, subjective workload, and SA.

In this study, two performance indices were included: the docking result and the control process. They were computed by a composite performance index. The docking result was a weighted summed score created by integrating final docking results, positional deviation, angular deviation, and relative velocity, which reflected the accuracy of the docking. The control process score was a weighted summed score created by integrating task duration and fuel consumption, which reflected the efficiency of the docking. The weighting coefficients had been established by previous studies using expert evaluation and other factor reduction methods,[9] ranging from 0 to 1 (a higher score indicating better performance). Docking results and control process are now used for evaluating real training performances.

The value of subjective workload was gathered from the NASA Task Load Index (NASA-TLX) which is a subjective, multidimensional assessment tool that rates perceived workload on six different subscales: Mental Demand, Physical Demand, Time Pressure, Performance, Effort, and Frustration. NASA-TLX is the most internationally used method for subjective workload assessment.[8] The subjects were requested to indicate, on a 10-point rating scale, for each of these dimensions and compare which subscale is more important from paired subscales.

The situation awareness rating technique (SART) is a widely used subjective report technique for the measurement of SA.[22] SART focuses on overall task characteristics rather than the specific elements related to the task.[23] It involves 10 questions to assess different items of SA. These items can be further combined as the following: 1) demand on attentional resources; 2) supply of attentional resources; and 3) understanding. Demand on attentional resources consists of questions regarding instability, complexity, and variability of the situation. Supply of attentional resources reflects on the level of arousal, concentration, division of attention, and extra mental resources in dealing with the situation. Finally, understanding of a situation reflects the quality and quantity of the information provided as well as the subject's familiarity with the situation. Scores of Demand, Supply, and Understanding can be derived by adding the score of the corresponding items. The overall SART score is then calculated using the following formula: SA = Understanding – (Demand – Supply).[11]

Procedure

The experiment required approximately 2 h of participation. Subjects first received an explanation of the test procedure and were then provided with necessary instructions upon arrival at the laboratory. They were required to sign a letter of consent. Then, a presentation of RVD task, control principle, control strategy, task requirement, and performance metrics were given to novice subjects by an RVD trainer. After the presentation, novice subjects were permitted to practice three chosen tasks in the pre-experiment. Expert subjects were permitted to practice the same tasks for refreshing RVD skill. Afterwards, each subject performed an identical set of six scenarios on the RVD simulator including two modes of tasks: manual RVD and the automation-aided RVD. The six scenarios differed in the initial relative position and orientation of the chaser and the target. The sequence of the experimental runs was balanced across subjects. At the end of each trial, subjects rated SA using SART, and workload using NASA-TLX. Each trial lasted for about 7 min and there was a 5-min break between two trails.

Statistical Analysis

The Shapiro-Wilk test and Levene's test were used to test whether the given data presented normal distribution. For all dependent variables, 2 (presence or absence of automation) $\times$2 (novice or expert group) repeated measures analyses of variance (ANOVAs) were calculated. If the interaction of automation and skill level became significant, a simple effect test was used to identify the effect of automation in novice and expert groups, respectively. Simple effects tests are follow-up tests when the interaction is significant. They explore the nature of the interaction by examining the difference between groups within one level of one of the independent variables. All analyses were carried out using SPSS software Release 20. An alpha level of 0.01 was used for all statistical tests. All values are presented as means $\pm$ SD. Mediation analysis was conducted following guidelines provided by Baron and Kenny to further investigate the inner relationship between mental workload as well as SA and performance.[3] Mediation analysis is usually used to identify and explain the mechanism or process that underlies an observed relationship between an independent variable and a dependent variable via the inclusion of a third hypothetical variable, known as a mediator variable. The mediator variable serves to clarify the nature of the relationship between the independent and dependent variables.

RESULTS

Effects of automation and skill level on performance merits were analyzed by a 2 (manual and automation aids condition) $\times$ 2 (group: novice group and expert group) repeated measure ANOVA and are shown in **Table I**. Effect of automation $\times$ skill interaction on the docking result was significant [$F(1,79) = 39.011$, $P < 0.001$]. A simple effect test for the docking result (**Fig. 1**) showed that the effect of automation on the docking result depended on skill level: the automation significantly increased the docking result of novice operators, [$F(1,76) = 124.14$, $P < 0.001$], while the docking result of expert operators didn't significantly change in the manual and the automation-aided condition, but showed a tendency to decrease the docking result in the automation-aided condition, [$F(1,76) = 1.38$, N.S.]. The effect of automation on control process was significant [$F(1,79) = 48.34$, $P < 0.001$]; automation significantly improved the efficiency of docking. The effect of skill on control process was significant [$F(1,79) = 208.50$, $P < 0.001$]; the experts significantly improved the efficiency of docking with less task duration and fuel consumption than the novices.

Effects of automation and skill level on NASA-TLX items are shown in **Table II**. Results showed effects of automation $\times$ skill interaction on subjective workload was significant [$F(1, 79) = 29.767$, $P < 0.001$]. The simple effect test (**Fig. 2**) showed that the effect of automation on subjective workload depended on skill level; the automation significantly decreased the subjective workload of novice operators, [$F(1,76) = 97.14$, $P < 0.001$], while subjective workload of expert operators did not change significantly in the manual and the automation-aided condition, [$F(1,76) = 0.79$, N.S.].

Effects of automation and skill level on SA rating items and subjective SA are shown in **Table III**. Effect of automation $\times$ skill interaction on demand of attentional resources, supply of attentional resources, understanding of situation and subjective SA became significant, [$F(1,79) = 7.136$, $P = 0.009$]; [$F(1,79) = 16.003$, $P < 0.001$]; [$F(1,79) = 13.680$, $P < 0.001$]; [$F(1,79) = 30.028$, $P < 0.001$], respectively. A simple effect test for demand on attentional resources (**Fig. 3**) showed that the effect of skill

Table I. The Effect of Automation and Skill on Performance Measures.

		SKILL LEVEL		*P* VALUE		
PERFORMANCE	LEVEL OF AUTOMATION	NOVICES	EXPERTS	AUTOMATION	SKILL	INTERACTION EFFECT
Docking result	M RVD*	0.58 ± 0.20	0.97 ± 0.05	<0.001	<0.001	<0.001
	AS RVD†	0.88 ± 0.11	0.93 ± 0.07			
Control process	M RVD	0.60 ± 0.08	0.87 ± 0.13	<0.001	<0.001	0.819
	AS RVD	0.71 ± 0.14	0.98 ± 0.06			

* M RVD was short for the manual rendezvous and docking.
† AS RVD was short for the automation-aided rendezvous and docking.

level on demand of attentional resources depended on the level of automation. Demand on attentional resources of expert operators was marginally significantly higher than that of novice operators in the automation-aided condition, [$F(1,76) = 2.92$, $P = 0.091$], while demand on attentional resources did not show a significant difference between novice operators and expert operators in the manual condition, [$F(1,76) = 0.16$, $P > 0.05$]. A simple effect test for supply of attentional resources (Fig. 3) showed that the effect of automation on supply of attentional resources depended on skill level; the automation significantly improved supply of attentional resources of novice operators, [$F(1,76) = 15.63$, $P < 0.001$], while supply of attentional resources of expert operators marginally significantly decreased in the automation-aided condition compared to manual condition, [$F(1,76) = 3.88$, $P = 0.052$]. A simple effect test for understanding of situation (Fig. 3) showed that the effect of automation on understanding of situation depended on skill level. Automation significantly improved understanding of situation for novices, [$F(1,76) = 7.59$, $P = 0.007$], while understanding of situation for experts marginally significantly decreased in the automation-aided condition compared to manual condition, [$F(1,76) = 3.41$, $P = 0.069$]. The simple effect test for SA (Fig. 3) showed that the effect of automation on SA depended on skill level. Automation significantly increased the SA for novice operators, [$F(1,76) = 53.69$, $P < 0.001$], while SA of expert operators did not change significantly in either the manual or the automation-aided condition, [$F(1,76) = 0.05$, N.S.].

Table IV shows the correlation between subjective workload and task performance, and SA and task performance. Zero-order correlation means a correlation between two variables which does not include a control variable. The two variables are not designated as dependent variable or independent variable. In terms of zero-order correlations, subjective workload and SA correlated with the docking result and control process for novices, respectively, but there was no correlation for experts.

The result of performance showed that the effect of automation on performance of novices was significant. This raises the question of whether automation and mental workload make independent contributions to predicting performance, or whether the effects of automation are mediated by mental workload. To investigate these questions, we conducted a series of regression analyses following guidelines provided by Baron and Kenny.[3]

Fig. 4A summarizes the results of the mediation analysis of subjective workload for the docking result in the novice group. In the first equation, we regressed the docking result on automation and found a significant relationship ($b = -0.560$, $P < 0.001$). In the second equation we regressed subjective workload (our proposed mediator) on automation, and again the relationship was significant ($b = -0.576$, $P < 0.001$). In the final equation, we regressed the docking result on both subjective workload and automation. In this equation, the association between subjective workload and the docking result was significant ($b = -0.590$, $P < 0.001$). Although the association between the docking result and automation was significant ($b = 0.220$, $P = 0.015$), the contribution of automation was reduced. Taken together, these findings suggest that subjective workload

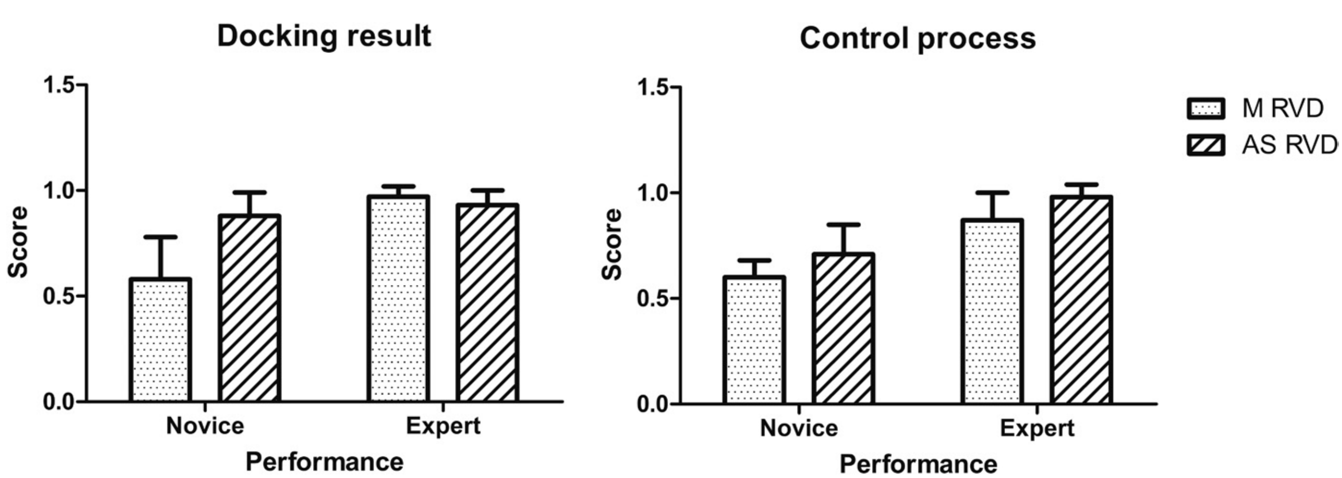

Fig. 1. The effect of automation and skill on performance (the error bars represent plus one standard deviation).

Table II. The Effect of Automation and Skill on Subjective Workload Items.

		SKILL LEVEL		*P* VALUE		
NASA-TLX ITEMS	LEVEL OF AUTOMATION	NOVICES	EXPERTS	AUTOMATION	SKILL	INTERACTION EFFECT
Mental Demand	M RVD*	5.86 ± 2.05	4.08 ± 2.57	<0.001	<0.001	<0.001
	AS RVD†	3.59 ± 1.87	3.77 ± 3.16			
Physical demand	M RVD	2.57 ± 1.55	2.41 ± 1.96	<0.001	0.797	0.617
	AS RVD	1.95 ± 1.64	1.92 ± 1.68			
Time pressure	M RVD	5.74 ± 2.23	2.56 ± 1.65	<0.001	<0.001	<0.001
	AS RVD	3.24 ± 2.02	1.89 ± 1.47			
Performance	M RVD	4.88 ± 2.45	2.00 ± 1.37	<0.001	<0.001	<0.001
	AS RVD	2.21 ± 1.60	2.00 ± 1.62			
Effort	M RVD	7.67 ± 1.49	7.53 ± 1.53	<0.001	0.103	<0.001
	AS RVD	6.02 ± 1.73	7.28 ± 1.84			
Frustration	M RVD	4.02 ± 2.35	1.53 ± 0.91	<0.001	<0.001	<0.001
	AS RVD	1.90 ± 1.37	1.42 ± 0.87			

* M RVD was short for the manual rendezvous and docking.
† AS RVD was short for the automation-aided rendezvous and docking.

partially mediates the relationship between automation and the docking result. The mediation analysis of subjective workload for control process failed to reveal the mediation effect of workload.

To investigate whether automation and SA make independent contributions to predicting performance, or whether the effects of automation are mediated by SA, we conducted a series of regression analyses.

Fig. 4B summarizes the results of the mediation analysis of SA for the docking result in the novice group. In the first equation, we regressed performance measures on automation and found a significant relationship (b = - 0.560, $P < 0.001$). In the second equation we regressed SA (our proposed mediator) on automation, and again the relationship was significant (b = 0.503, $P < 0.001$). In the final equation, we regressed performance measures on both SA and automation. In this equation, the association between SA and positional deviation was significant (b = 0.348, $P < 0.001$). Although association between the docking result and automation was still significant (b = 0.385, $P < 0.001$), the contribution of automation was reduced. Taken together, these findings suggest that SA partially mediates the relationship between automation and the docking result. For performance measures of task time, the partial mediation effect of mental workload was found. The mediation analysis of SA for control process failed to reveal the mediation effect of SA.

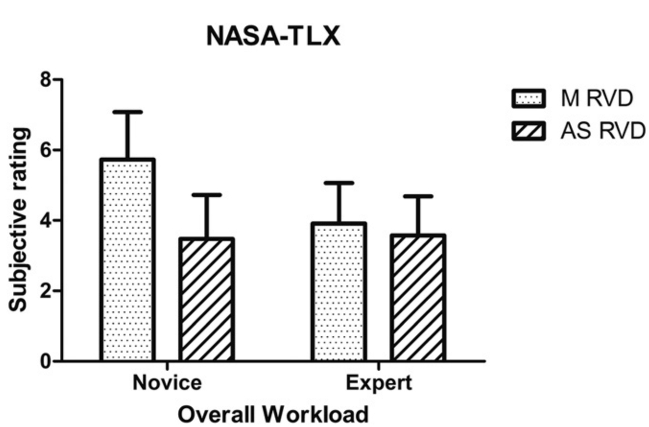

Fig. 2. The effect of automation and skill on overall workload (the error bars represent plus one standard deviation).

DISCUSSION

The purpose of the present study was to investigate the influence of automation aid in RVD task on performance, workload, and SA across novice and expert groups.

Firstly, it was found that the performance gap between novice and expert was decreased with the aid of automation. The same phenomenon was found in driving studies.[28] The reason may be the following: novices are not familiar with the task scenario and control strategy and have not formulated a correct mental model, thus exhibiting poor performance. The automatic RVD system could reduce the orientation deviation as soon as the deviation was detected and achieve a better docking accuracy than that of novices. Therefore, the performance of novices in the automation-aided condition was much better than that in the manual condition. Experts, who had formed the direct connection between the primary information and action, simplified the cognitive process, and formulated a corresponding mental model, thus gaining little benefit from automation. The results were supported by the limited resources theory which suggested that performance should be improved by automation only if the task exceeds the capacity of the human operator.[27] The result that the skill gap between novice and expert was attenuated with the introduction of automation indicated that astronauts with less training may perform RVD tasks with the aid of automation. However, it is important to note that automation may improve their performance in the short-term, but if they do not possess the manual skill to react when automation fails, there will be no automatic reactions to an abnormal situation.[19] Moreover, the results also showed that some of our current understanding of automation derives from nonprofessional performers, but findings based on these people cannot be readily extrapolated to more experienced, professional operators.

Table III. The Effect of Automation and Skill on SA.

SA[‡]	LEVEL OF AUTOMATION	SKILL LEVEL		*P* VALUE		
		NOVICES	EXPERTS	AUTOMATION	SKILL	INTERACTION EFFECT
Demand	M RVD*	65.08 ± 12.38	63.89 ± 14.23	<0.001	0.406	0.014
	AS RVD[†]	52.95 ± 12.76	59.13 ± 18.96			
Supply	M RVD	57.94 ± 11.32	78.97 ± 8.24	0.219	<0.001	<0.001
	AS RVD	63.09 ± 10.69	76.19 ± 7.11			
Understanding	M RVD	65.65 ± 10.16	79.46 ± 10.64	0.607	<0.001	0.002
	AS RVD	69.34 ± 8.75	76.78 ± 12.53			
SA	M RVD	58.50 ± 20.84	94.54 ± 17.52	0.001	<0.001	<0.001
	AS RVD	79.49 ± 18.30	93.85 ± 20.43			

* M RVD was short for the manual rendezvous and docking.
[†] AS RVD was short for the automation-aided rendezvous and docking.
[‡] Demand was short for demand on attentional resources; Supply was short for supply of attentional resources; Understanding was short for understanding of the situation.

Secondly, automation decreased the subjective workload for novices, but did not influence that of experts significantly. This led the subjects in the novice group to implement tasks with better accuracy and stability by the aid of automation than manual controlling. It could be that novice subjects were already beyond their capacity limit in the manual operation and the automation contributed to bringing their mental workload within manageable levels. The extra capacity in manual and automation-aided conditions was different for novice operators, reflecting their lack of skill in the manual task. Experts reported the same level of subjective workload in the automation-aided condition as that in the manual condition. It could be that the cognitive processing of experts is more automatic, which is characteristically fast, unconscious, and almost completely liberated from attentional resource constraints.

Moreover, the benefits of automation for novices also lead to increased SA, including decreased "demand on the attentional resources" as well as increased "supply of attentional resources" and "understanding of the situation" in the automation-aided condition. The effect of automation on SA of experts included the tendency to decrease SA, reflected by the decreased "supply of attentional resources" and "understanding of the situation." The reason for the effect of automation on novices may be that reducing parts of the novices' task might plausibly be associated

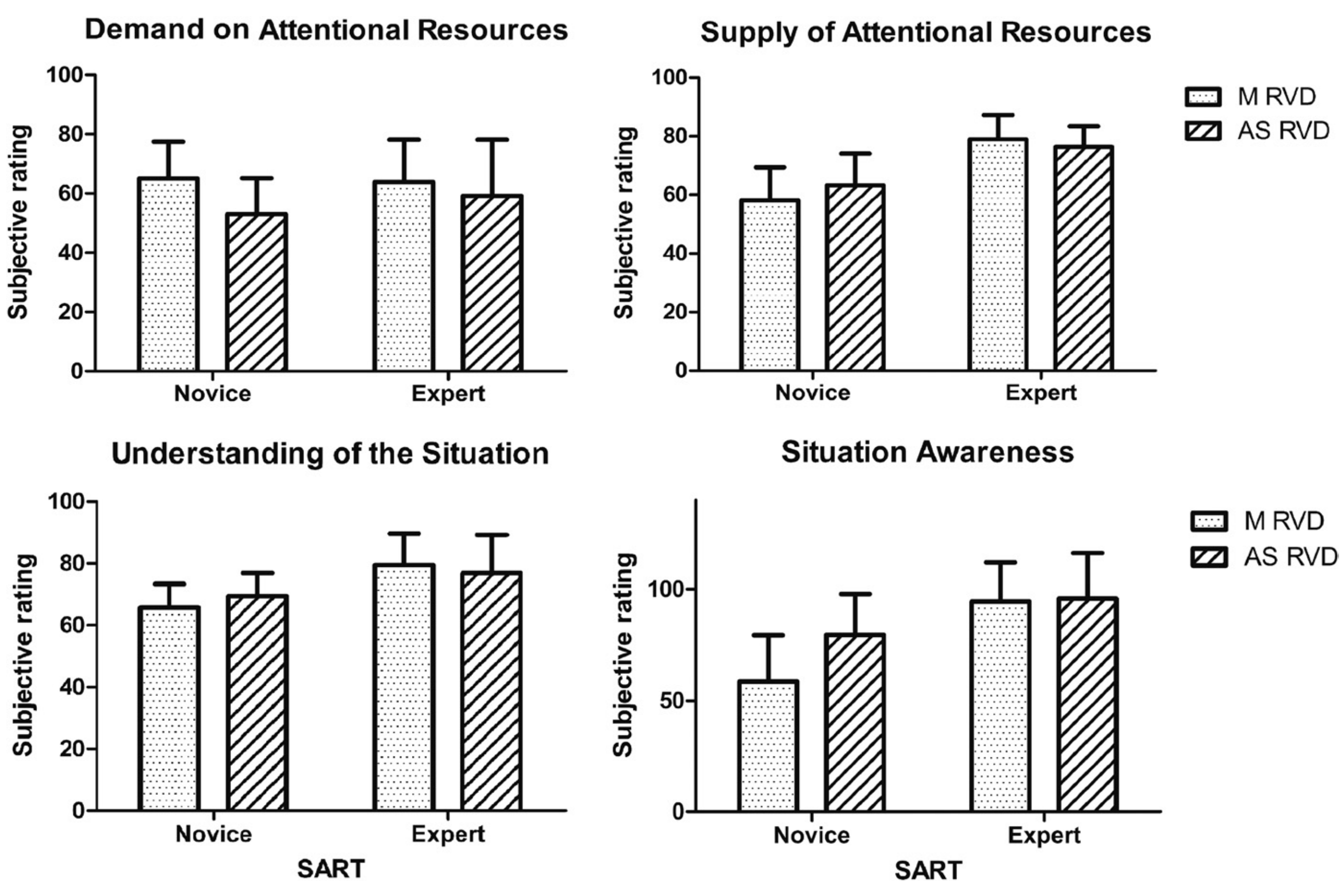

Fig. 3. The effect of automation and skill on SA (the error bars represent plus one standard deviation).

Table IV Descriptive Statistics and Zero-Order Correlations.

		MEAN	SD	1	2	3
1. Subjective workload†	Novice	4.73	1.87	-	-	-
	Expert	3.74	1.16	-	-	-
2. Docking result†	Novice	0.73	0.22	-0.625**	-	-
	Expert	0.95	0.06	-0.095	-	-
3. Control process†	Novice	0.66	0.12	-0.226*	0.358**	-
	Expert	0.92	0.11	-0.011	-0.160	-
4. SA‡	Novice	68.51	22.30	-		-
	Expert	94.20	18.90	-		-
5. Docking result‡	Novice	0.73	0.22	0.571**	-	-
	Expert	0.95	0.06	0.037	-	-
6. Control process‡	Novice	0.66	0.12	0.208*	0.358**	-
	Expert	0.92	0.11	-0.112	-0.160	-

† Numbers 1∼3 were the descriptive statistics and zero-order correlations of workload and performance.
‡ Numbers 4∼6 were descriptive statistics and zero-order correlations of SA and performance.
* Significance level is 0.05.
** Significance level is 0.01.

with increased SA as they have potentially greater opportunities to seek information and process it. For experts, the decreased SA may be caused by removal of the experts from the task of orientation control. In classic ergonomics research, this is referred to as out-of-the-loop control, which is characterized by a decreased ability of the human operator to intervene in system control loops and assume manual control when needed in monitoring automated systems.[15] In out-of-the-loop control, there is no longer any requirement for the operators to attend to the feedback as they do not need it to control the spacecraft, and the passive role of monitoring an automatic system is less satisfactory from a human performance perspective than the active role of controlling it,[12] in which complacency may also be involved.[18] Currently, the design of the automation system in RVD was based on function allocation concepts, which delineate the roles of human and machine in a task-based manner. In this model, the complexity, understandability, and predictability of automation prevents human operators from collaborating with automation.[14] Therefore, researchers insisted that automation should support the human operators rather than replace them,[21] and applied the concept of cooperation and teamwork to enrich the human-machine dynamic.[11] Astronauts encounter more complex, multipart tasks in current high pressure, high-demand working environments. Traditional function allocation studies whether a particular function/task will be accomplished by a human, technology (hardware or software), or some combination of human and technology. This usually includes spatial (allocation of shared task space) and temporal (working time sequence for human and/or technology) function allocation. The results in our study showed that the improvement of performance by automation was different between the novice and expert groups, which provided a new viewpoint for function allocation and encouraged people to explore the different forms of human-machine cooperation.

This study investigated the effect of automation on performance, workload, and SA. While performance is a crucial result in complex human-machine systems, workload and SA were more important in the efficiency and reliability of the task. This raises the question of what the relationship between automation, workload, SA, and performance was. The mediation analysis of workload as well as SA and the docking result for novices suggested that the impact of automation on the docking result is partially mediated by workload and SA. However, no such mediation effect was found in the expert group. It could be that automated aids freed the novice operators from certain activities. This unloading is expected to free information-processing resources, which may directly reduce the workload of operators, or which can be used for other tasks. This may be the reason for improved performance in the automation-aided condition. And the improved SA may be conducive to the operation, and lead to enhanced performance. The results of the expert group may be because the workload and SA level of experts was rather moderate, at which performance normally remains constant until spare attentional capacity is nearly exhausted.

Overall, this study showed that the performance gap between novice and expert was decreased with the aid of automation. Moreover, automation can reduce subjective workload and enhance SA for novices, but potentially lower expert performance, and harm the SA. Further analysis showed that the impact of automation on novices' performance was partially mediated by workload and SA. However, no such mediation effect was found in the expert group. There was an interesting but important finding that automation can be detrimental to

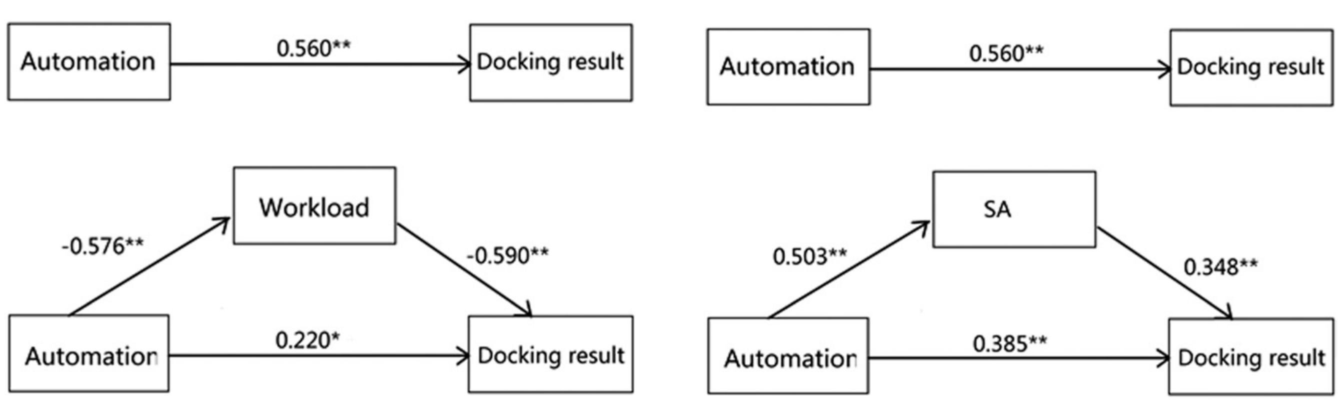

Fig. 4. A (left). Mediation analysis of subjective workload for the docking result in the novice group. **B (right).** Mediation analysis of SA for the docking result in the novice group. *Significance level of 0.05; **significance level of 0.01.

various elements of the functioning of highly trained/experienced operators, thus impairing their SA ability and increasing their mental workload. Attention and its functioning in relation to working memory and the relationship between SA and workload were not discussed here; these would be considered in future research.

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