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Automation of Sensor Control in Uninhabited Aerial Vehicles

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ABSTRACT

The use of automation in uninhabited aerial vehicles (UAVs) is being explored using simulation to develop a better balance of system autonomy with human interaction for optimal human-system performance. Integrating fixed levels of automation into elements of UAV control has resulted in improved performance of some tasks, but less so when the automation does not fit appropriately to changing UAV tasks and environments. As a consequence, recent research has focused on automation that can be changed during UAV operation. The aim of this study was to compare the performance of operators for some UAV tasks of interest under automation that could be changed (adaptable), fixed automation, and no automation. A secondary aim was to examine the use of automation and its effect on the performance of these tasks in different area densities. Thirty eight participants from the Defence Science and Technology (DST) Group Edinburgh controlled the sensor of an UAV and undertook typical tasks in a maritime environment. Sensor control was manipulated to be fully automated (fixed), completely manual, or adjustable by the participant between automated and manual modes (adaptable). The results showed that fixed sensor control produced superior performance compared to manual control across tasks, but adaptable control produced additional time improvements compared to fixed control. The benefits of adaptable automation of sensor control and future research directions are discussed.

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Automation of Sensor Control in Uninhabited Aerial Vehicles

Executive Summary

The use of automation in uninhabited aerial vehicles (UAVs) is currently being explored in using simulation to develop a better balance of system autonomy with human interaction for optimal human-system performance. Integrating fixed levels of automation into elements of UAV control has shown improved performance of some tasks, but less so when the automation does not fit appropriately to changing UAV tasks and environments. As a consequence, recent research has focused on automation that can be changed during UAV operation, otherwise termed adaptable automation.

This report describes a human-in-the-loop simulation study conducted to extend the knowledge of using adaptable automation in UAVs. The research formed the basis of a master's thesis completed through the University of Adelaide under a Graduate Industry Placement arrangement with the Defence Science and Technology (DST) Group. Its purpose was to inform UAV use by the Royal Australian Navy. The objectives of the study were to compare the differences in performance of UAV tasks under automation that could be changed, automation that was fixed, and no automation during operation. A secondary objective was to examine the use and effect of automation on performance of tasks in different area densities.

Tasks were designed to be representative of those conducted in a maritime context, and involved reporting details about a specific surface vessel in a particular area as well as reporting on the total number of surface vessels in that area. Participants were also required to acknowledge changes in system status gauges when they occurred. The automation conditions were tested at the camera level of control, otherwise referred to as the sensor, and as such all flight and navigation of the UAV was predetermined by the system. Sensor control conditions were manipulated such that participants performed the reporting and system status tasks when the sensor was controlled manually, when it was fully automated and could not be controlled by the participant (fixed), and when participants could switch between full automation and manual control (adaptable). The area density was also manipulated by changing the total number of vessels in each area.

It was found that fully automating the sensor control improved reporting performance compared to when participants had to operate the sensor manually. Additionally, when participants could freely switch between manual and fully automated sensor control, improved reporting performance was also found compared to when only manual control was available. When the automation could be changed during operation, participants produced the fastest reports overall but the error rate remained no different to that when the sensor was fully automated.

These findings suggest that adaptable automation at the sensor control level should be employed for superior performance of operator tasks in this setting. It is proposed that expanding the number of operator tasks in future simulations could build on the benefits of adaptable automation use identified in the current study, as well as highlight its potential impacts.

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Contents

Acronyms

ANOVA	analysis of variance
HUD	Heads Up Display
LOA	level of automation
MBC	management by consent
MBE	management by exception
SME	subject matter expert
UAV	uninhabited aerial vehicle
VOI	vessel of interest

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1. Introduction

Uninhabited Aerial Vehicles (UAVs) have become indispensable assets in defence organisations around the world allowing reduced radar signatures, increased endurance, and most importantly the removal of humans from immediate threat (Hopcroft, Burchat, & Vince, 2006; McCarley & Wickens, 2005). With exponential increases in technology over the past two decades, today's UAVs are highly automated and can be directed to follow a pre-programmed mission, fly to designated coordinates, fly specific patterns, correct for course deviations, and hold above a particular coordinate or target (Arrabito et al., 2010).

It is argued that increased UAV automation provides benefits such as simplified operations, lower operating costs, and reduced operator workload (Arrabito, et al., 2010). However, one significant consequence of automation is the altered role of the human operator from manual control to supervisory or managerial control of the UAV (Parasuraman, Molloy, Mouloua, & Hilburn, 1996). As a result, the operator may have to evaluate or finalise automated decisions, diagnose problems, and take over manually when the automation fails (Arrabito, et al., 2010).

With the advent of increased levels of automation (LOA) within UAV systems, there has been increasing effort to design systems to remove the need for multiple operators to control one vehicle and instead have one operator control multiple vehicles (Cummings, Bruni, Mercier, & Mitchell, 2007; Dixon, Wickens, & Chang, 2005; Ruff, Narayanan, & Draper, 2002). However, single operator control of one or even more autonomous vehicles needs to be evaluated to address the balance of system autonomy with human interaction for optimal human-system performance.

1.1 Automation

The role of automation in systems has challenged the research community for over 50 years with a range of pragmatic and philosophical issues, namely the failure of automation to achieve its promised benefits and how automation redefines the role of humans in complex systems (Lee, 2008). The literature on human-automation interaction is extensive, however some key issues have emerged that have been termed by Parasuraman and Riley (1997) as human's use, misuse, disuse, and abuse of automation. These issues are still relevant over 10 years later, despite major technological advances during this period, and will be discussed (Lee, 2008).

With regard to human's *use* of automation, it is commonly thought that the user's engagement in automation to perform functions that were otherwise performed manually reduces workload and mitigates high workload situations. On the other hand, it has been suggested that the apparent simplicity of automation can also mask its actual complexity, which is only revealed in demanding situations (Woods, 1996; Woods & Dekker, 2000).

Problems may arise when humans rely on poorly performing automation through excessive trust in the automation, engage automation in situations that are not appropriate for doing so, or fall prey to automation biases that make them less attentive to contradictory information: factors that all contribute to humans' *misuse* of automation. Of particular relevance in this concern is the monitoring of failures, whereby humans tend to neglect automation breakdowns. Typically, the less likely a failure is to occur the more likely the human operator will not detect an automation breakdown when one actually occurs (Lee, 2008).

In the domain of *disuse* of automation, humans fail to engage in automation where it could enhance performance. In this way, humans can be slow to accept automation as it may threaten their way of working, they may have not developed an appropriate level of trust in its capability, or the automation lacks the needed functionality (Lee, 2006). Warnings also play a role in this area; a high rate of false alarms in systems is likely to undermine acceptance and lead to disuse (Bliss, 2003).

Abuse of automation has been described as situations in which automation is designed and implemented without paying sufficient attention to its effects on the operators, in an effort to replace unreliable people with reliable automation. Here exists a "replacement fallacy" (Lee, 2008, p. 407), by which the assumption exists that failures can be avoided by automating the operator's role, however this ultimately ignores the role people play in accommodating the unexpected and preserving an efficient system (Woods & Dekker, 2000).

1.2 Conceptualising UAV automation

A practical model for understanding how automation plays a role in UAV control has been provided by Cummings et al. (2007) as shown in Figure 1. Human supervisory control of UAVs is hierarchical, depicted by lower and higher level control loops. The innermost and therefore the lowest-order loop is flight control of the UAV. Within this loop, control of the UAV is limited to basic guidance and motion control, whereby short-term goals such as keeping the aircraft in stable flight are the focus. The navigational loop is depicted as the second-order loop in the hierarchy, and attends to mission constraints such as routes to coordinates, time on targets, and avoidance of threat areas and no-fly zones. The highest-order loop is represented by mission and payload management whereby incoming information from sensors must be monitored in order to make decisions and meet overall mission requirements. An additional system health and status monitoring loop is integrated over all of the control loops, and its order is flexible within the hierarchy as depicted by its dotted line. For example, should system health decline to a critical level, tasks within this loop may take the highest priority, however when system health is normal monitoring the system status may only be intermittent and secondary to other prioritised tasks within the hierarchical control loops. The authors have suggested that, for a single UAV operator, by automating tasks required in lower order control loops, task demand and cognitive reserve can be freed up to attend to tasks in higher order control loops.

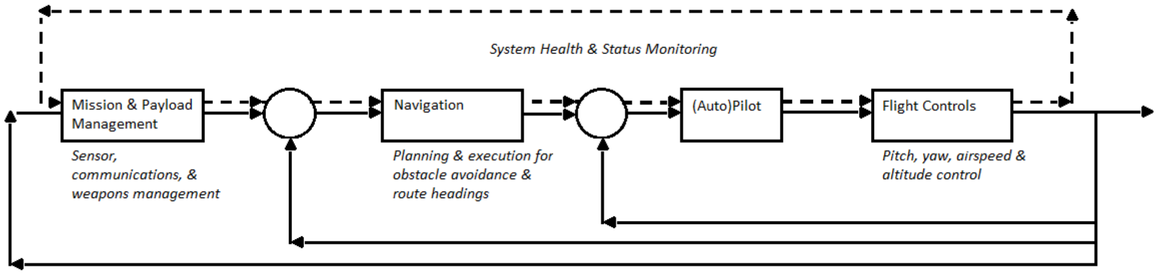

Figure 1: Hierarchical Control Loops for a Single UAV (Cummings, et al., 2007 pp. 4)

1.3 Automation in UAVs

Research using simulation to examine automation in UAV systems has suggested that automating some tasks required of UAV operators can improve performance across other tasks. Wickens and Dixon (2002) had participants locate surface objects in the sensor's field of view (FOV) while an UAV was in flight. In addition, Wickens and Dixon (2002) also required participants to monitor for system status changes depicted by gauge needles that would move from a green to a red zone indicating a system status failure. Participants had to press a "detect" button on the joystick, then use a keypad to input which system had failed and a required coordinate. If the system status failure was not detected within 30 seconds, then the gauge needle would move back to the green zone. The flight control loop of the UAV was completely automated, and automation was experimentally manipulated in the navigational loop of the UAV. In one condition participants also had to maintain the UAV on a straight flight path to a particular set of coordinates by manipulating the joystick left and right along its x-axis, while in another condition participants previously inputted "fly to" coordinates that had the UAV fly directly to those coordinates without requiring maintenance from participants to stay on the straight flight path. Sensor manipulation was the same across both conditions whereby it was controlled via y-axis movement of a joystick. Participants could manipulate the sensor to view straight down to the land surface below or pan up to 45 degrees toward the horizon.

Compared to those having to maintain the UAV along the straight flight path, those that had the UAV fly the path automatically were subsequently better at detecting required surface objects with the sensor (60% versus 90% detected respectively). This suggested that automating the navigational requirement of operators in this context freed up task demand and subsequent cognitive reserve to allow improved surface search detection. Task demand was reduced for those with automated navigation as they were not required to manipulate the joystick along its x axis, but rather only focus on y axis movement of the sensor. Additionally, a higher proportion of system status failures was detected and processed for those with automated navigation, although system status processing times between those with automated navigation and those without did not differ. Overall, Wickens and Dixon (2002) provided evidence that the performance of operators, in tasks beyond the navigational requirements of the UAV, would likely be hindered without automated navigation assistance. These findings are also in line with Cummings et al. (2007) UAV control model, where higher level sensor control operation and mission requirements were degraded by lower level flight and navigation requirements.

Building on the study by Wickens and Dixon (2002), Dixon et al. (2005) assessed operators in exactly the same experimental conditions as in the former study, with the exception of including a comparison of performance measures between operators of two UAVs and operators of one UAV. Again it was found that when controlling one UAV, detection of required surface objects was superior for operators with automated navigation compared to those without (92% versus 79% detected respectively). This trend also remained for this task when controlling two UAVs (76% versus 52% detected respectively). However, there was a significant drop in detection of required surface objects overall when controlling two UAVs compared to one UAV. This indicated that while automating navigation in this context still improved performance on a surface search task compared to no navigation automation, this task was negatively impacted by the introduction of two UAVs to be controlled. Under dual UAV control, workload was essentially doubled and surface search ability deteriorated. It was proposed that for controlling two UAVs or potentially more, automation might also need to be applied at the highest-order control loop of sensor control and decision making (Cummings, et al., 2007) to further assist in reducing operator workload and performance deterioration.

As opposed to a methodology of completely automating some tasks or not within UAV systems, other research has examined levels of automation (LOAs) for particular tasks along a continuum. A framework has been outlined from no automation (the human operator makes all decisions and takes all actions), through management-by-consent (MBC; the system suggests a course of action or small set of alternatives from which the human accepts or rejects or chooses a preferred course of action), and management-by-exception (MBE; the human is informed of the system's intentions and given the opportunity to veto these actions within a set time frame), to complete automation (the system makes all decisions and takes all actions) (Parasuraman, Sheridan, & Wickens, 2000).

Some research examining this approach to automation in UAVs has found a management-by-consent LOA to be most effective for balancing system autonomy with human interaction for optimal human-system performance (Liu, Wasson, & Vincenzi, 2009; Prinet, Terhune, & Sarter, 2012; Ruff, et al., 2002). Ruff et al. (2002) had participants operate UAVs to seek and destroy required surface targets. Although the flight control loop was completely automated, prompts were provided to participants. A prompt was provided when the fuel of the UAV had reached a level where a return to base was necessary, the airspeed had approached a stall speed, or when the altitude had approached a maximum or minimum. If participants accepted the prompt, the system would implement the required corrective action to the problem. The navigational control of the UAVs was done via waypoints; directional drag-and-drop lines over a two dimensional map of an area which then depicted the flight path of the UAV. All participants manipulated waypoints so that the UAVs flew to the surface targets which were also depicted on the two dimensional map of the area. The authors did not mention any human-system interaction with regard to the sensor control, so it was assumed this process was actioned by the system. Users could traverse an additional three-dimensional map of the area, much like an invisible spectator, in order to view the environment of the area, but this was artificially created for the simulation and not a view from the sensor on an UAV itself. Despite this lack of detail, the authors included a prompt in the mission and payload management control loop whereby the system notified the operator when a surface target was detected by an UAV. If participants accepted the prompt, the system would shoot the target when it was within shooting range.

Ruff et al. (2002) implemented three conditions in their study. A MBC condition involved the system offering participants all prompts as described, but no action would be taken unless participants had accepted the prompt. On the other hand, a MBE condition involved all the same prompts existing as in the MBC condition, but the system automatically acted after three seconds unless participants rejected the prompt prior to the action. The authors also referred to a baseline condition, termed as a manual condition, but did not explicitly describe what this was. No prompting existed in this condition, and it was assumed that operators were then required to monitor gauges of flight control and manipulate waypoints accordingly, as well as manually implement the shooting of targets. Nonetheless, Ruff et al. (2002) reported greater mission efficiency from those in the MBC condition compared to those in the manual and MBE conditions, although caution should be exercised when interpreting this finding. Mission efficiency was defined as the total number of surface targets destroyed divided by the total number of missiles fired, yet it was not made explicit by the authors how operators might have fired more missiles than surface targets, and specifically how this performance measurement could be affected by a LOA being applied. Ruff et al. (2002) also reported a reduced number of "hit points" (Ruff, et al., 2002 pp. 343) for those in the MBC condition compared to those in the manual and MBE conditions. If an UAV was navigated to within "100 units" (distance of a unit was undefined; Ruff, et al., 2002 pp. 343) of a surface target, this was defined as a violation, and one hit point was received for every 250 milliseconds of violation. The findings suggested that applying more automation, or moving to a higher LOA such as MBE, in a human-system UAV design may not always improve overall human-system performance. Additionally, Ruff et al. (2002) pointed out that their participants actually preferred the MBC condition compared to the two other conditions, and suggested that this LOA assisted participants in attending to tasks but effectively maintained their awareness of the system's events and activities being performed.

Other research (Liu et al., 2009) has supported findings from Ruff et al. (2002) that MBC might be a more appropriate approach compared to MBE for optimal human-system performance in UAVs. Liu et al. (2009) had participants monitor incoming images taken from the sensors of UAVs. In this simulation research, many of the UAV functions were already completely automated. All flight, navigation, and sensor controls were actioned by the system. An "Automatic Target Recognizer (ATR)" (Liu, et al., 2009 pp. 799) in the system placed a red box around suspected targets in the images taken from the UAV sensor. The ATR was 80 per cent reliable, thus if its actions were incorrect the participant had to add or delete red boxes on the images themselves. In a MBC condition, participants were prompted to accept or reject images. If accepted, the image was removed and the next image from a queue of images that had been taken by the sensor would appear. The authors were unclear in describing the reject function, but presumably rejecting the image would allow manipulation of the red boxes, after which the image could be accepted. Participants in the MBC condition were compared to those in a MBE condition, whereby the system automatically accepted the image after 15 seconds unless the participant intervened earlier or pressed a hold button to allow more time. Liu et al. (2009) found that those in the MBC condition yielded shorter image processing times than those in the MBE condition, although there were no differences in error rates between conditions.

Further to Ruff et al. (2002) and Liu et al. (2009), recent research by Prinet et al. (2012) had participants undertake a surface target detection and a route-replanning task. In the surface detection task, participants had to monitor video feeds from UAVs as they were approaching areas where a target might have been present, and responded by pressing a corresponding button on the system if they detected a target, were unsure if there was a target, or were confident that no target was present. In the route-replanning task, circumstances would change in the environment, which included the addition/removal/moving of a target, activation of no-fly zones, poor weather conditions, or a fuel leak on an UAV, which required participants to replan a route for an UAV. The lowest order flight control and highest order sensor control loops were actioned by the system, while navigational control was actioned by drag and drop waypoints. In one MBC condition, labelled "intermediate" (Prinet, et al., 2012 pp. 424), participants could replan an UAV's waypoints by choosing one of three different replanning options generated by the system in response to the environmental change. Alongside each of these options were three 10-point scores with 10 being the best possible score. The first score represented the time for the UAV to reach base, the second represented the risk of the UAV being shot down, and the third represented the percentage of targets visited at the time the replanning options were generated. In another MBC condition, labelled "automated" (Prinet, et al., 2012 pp. 424) participants could replan an UAV's waypoints by choosing one different replanning option with its three 10-point scores generated by the system. For both MBC conditions, participants could accept a new proposed set of waypoints for an UAV, or the original flight path would remain active if the participant rejected the proposed flight path. In addition to the two MBC conditions, a "manual" condition was included (Prinet, et al., 2012 pp. 424) whereby the system did not generate replanning options and participants had to drag and drop new waypoints to address the environment change that required replanning.

Prinet et al.'s results (2012) followed trends reported in previous research (Liu, et al., 2009; Ruff, et al., 2002), finding that participants in the two MBC conditions correctly identified more surface targets and had shorter replanning times than those in the manual condition. On the other hand, the authors also found some contradictory results, whereby those in the MBC conditions had the largest proportion of UAVs shot down as a result of being present in no-fly zones compared to those in the manual condition. Here the authors pointed out a common problem with not being able to change a LOA when attending to a particular UAV task. In their study, no-fly zones were updated through the use of a live chat box from mission command. Known no-fly zones were inputted into the system prior to the mission commencing, thus the system could calculate routes for the UAVs accordingly, but changes from live updates were not able to be programmed into the system. As a result, participants in the MBC conditions with only the option to continue an UAV along its original flight path or accept a new one generated by the system were at greater risk of directing the UAV into a no-fly zone compared to those who could freely manipulate flight paths at any time in the manual condition.

One of the challenges in determining the appropriate balance of system autonomy with human interaction for optimal human-system performance is that different tasks have been automated in different studies, with little overlap between studies to enable direct comparison. Tasks have varied from surface object recognition (Dixon, et al., 2005; Wickens & Dixon, 2002), to seek and destroy operations (Ruff, et al., 2002), image analysis

(Liu, et al., 2009), and target detection (Prinet, et al., 2012), and complexity has been further introduced by applying different LOAs on these tasks. Nonetheless, several trends are apparent. Firstly, following Cumming et al.'s (2007) hierarchical control loop, complete automation of the flight control loop and some automation of the navigation control loop may serve for better human-system performance of tasks in the mission and payload loop (Dixon, et al., 2005; Wickens & Dixon, 2002). Secondly, applying automation in the navigation and mission and payload loops may assist human-system performance on particular tasks, but the LOA applied may impede this performance if the system acts without human involvement (Liu, et al., 2009; Ruff, et al., 2002) or is not responsive to changes in the environment (Prinet, et al., 2012).

1.4 Adaptable automation

A criticism of applying a LOA to assist human-system performance has been that once a LOA is designed into a system it cannot be changed during operation, and thus it is fixed (Miller, Funk, Goldman, Meisner, & Wu, 2005; Miller & Parasuraman, 2007). This is of particular concern for the operation of UAVs, whereby changing environments and tasks may demand more or less interaction from the user with elements of the system at varying times, but the applied LOA does not correspond with these changes. To accommodate changing environments and tasks of UAV systems, flexible automation has been investigated, which allows LOAs to change based on user need and workload demand. Two types of flexible automation within UAV systems have been researched; those that are system driven (adaptive) and those that are user driven (adaptable) (Miller, et al., 2005). Adaptive automation, based on pre-defined rules built into the system, shifts elements of the system into a lower or higher LOA depending on operator interaction and frequency of inputs. Conversely, in adaptable automation the user shifts elements of the system into a lower or higher LOA when they deem appropriate. Miller, Pelican and Goldman (2000) compared adaptive and adaptable automation and concluded that adaptive automation may have the advantage of reducing workload when needed, but may also result in increased unpredictability in the system given the user has no control over the changes in LOA that may occur (Billings & Woods, 1994; Sarter, Woods, & Billings, 1997). Adaptable automation, on the other hand, may have the advantage of reducing unpredictability of the system as the user can knowledgably choose a LOA when required. However, adding the task of setting a LOA to the user's list may also inadvertently increase his/her workload (Bailey, Scerbo, Freeman, Mikulka, & Scott, 2006).

Adaptive automation has led to improved performance on some UAV tasks over no automation (e.g. Hou, Kobierski, & Brown, 2007; Parasuraman, Cosenzo, & De Visser, 2009) and fixed automation (e.g. Calhoun, Ruff, Spriggs, & Murray, 2012; Parasuraman, et al., 2009), but very little empirical research has examined adaptable automation in an UAV context, particularly in comparison to fixed automation. One study has recently suggested that adaptable automation may be more beneficial than adaptive automation. Kidwell, Calhoun, Ruff, and Parasuraman (2012) had participants monitor a two dimensional map that depicted UAVs flight paths, and required them to detect and acknowledge the appearance of a map symbol representing a hostile aircraft if one appeared at any time. The authors also tasked participants with counting the number of specified targets in images taken from the sensors of the UAVs. As in Liu et al.'s (2009) study, images were taken by UAVs and a 90% reliable ATR was used to estimate the number of specified targets in each image. Kidwell et al (2012) had all flight control, navigation, and sensor control actioned by the system. In an adaptable condition, the LOA of the ATR started in a low automated setting, whereby the number of specified targets in the image had to be inputted by the participant. If the ATR was moved to a medium setting, the system provided a recommendation as to the number of specified targets in the image. If the ATR was moved to a high setting, the system also provided a recommendation as to the number of specified targets in the image, but inputted this number for the participant after 20 seconds unless the participant vetoed the action prior to this time. In the adaptive condition, the LOA of the ATR also started in the low setting, but changed according to pre-built rules on processing times for the required tasks.

In their research, Kidwell et al. (2012) noted that for the highest prioritised task, detecting and acknowledging a hostile aircraft, detection rate was significantly higher for participants in the adaptable compared to the adaptive condition, suggesting that the act of delegating the LOA may have served to better keep the operator aware of and alert to unexpected stimuli. Interestingly, the authors reported a greater, although not statistically significantly so, mean response time in the detection and acknowledgement task in the adaptable compared to the adaptive condition. Greater cognitive resources may have been demanded by those participants who had to delegate a LOA, resulting in slightly increased processing time. However, it appeared that a loss of speed was traded for improved accuracy in this condition. For the image analysis task itself it does not appear that a speed accuracy trade-off existed. The authors reported a slightly slower, although non-significantly so, task completion time in the adaptable compared to the adaptive condition, but failed to find any difference between conditions with regard to image analysis accuracy.

Other research has also looked at the human delegating LOAs compared to no automation. Shaw et al. (2010) had operators control three UAVs to detect and track specific surface vehicles within three designated areas. If a specific surface vehicle travelled to an armoury location to become weaponised, operators had to prosecute the surface vehicle via control of the UAVs. An additional task required by operators was to identify and mark or “paint” (Shaw, et al., 2010 pp. 1499) civilian vehicles in the designated areas. In their study, all flight control of the UAVs was automated, navigation was controlled via manipulation of waypoints, and sensor control was managed by the operator via joystick manoeuvring. The authors compared the performance of operators under manual control to that of operators who were able to implement a switch to a LOA. Under manual control, operators had to drag and drop waypoints to implement flight paths for the UAVs, and had to manipulate the sensor in order to detect and track specific surface vehicles in the designated areas. Additionally, those in the manual condition had to manually task prosecution of the specific surface vehicle if it became weaponised. In a second condition, operators could switch between manual and a high LOA. The high LOA permitted three “plays” (Shaw, et al., 2010 pp. 1450), which included setting all UAVs on automatic flight paths with the sensors slewed to continually hold the entire designated areas in their FOVs, setting the UAVs to automatically prosecute a weaponised surface vehicle, or setting the first option with the exception of manoeuvring the sensor of one UAV. In a third condition, manual and a high LOA were available for use, as well as an intermediate LOA. The intermediate LOA allowed participants to scroll through one UAV at a time and set an automatic flight path with a slewed sensor on the designated area. These three conditions were assessed across two workload conditions changing the number of civilian vehicles presented. In a low workload condition, 19 civilian vehicles were presented, while in a high workload condition 64 civilian vehicles were presented.

Shaw et al. (2010) found that tracking accuracy, measured as the number of vehicles that were actually tracked against the number that could potentially be tracked, was significantly better in the third condition, where all LOAs were available for the operator to shift between, compared to the first or second condition (61.7% versus 46.1% and 49.4% respectively). Although the authors did not report which LOA the simulation started in or whether shifts were actually made by operators who had the option of using a LOA, these findings suggested that operators with three LOAs available for use were better able to perform a required task than were those who had no automated assistance or only one LOA to shift to.

Additionally, Shaw et al. (2010) also found that participants with all LOAs available for use were faster in dealing with an unexpected event compared to those with only one LOA to use or no automated assistance. The unexpected event was a pop-up target which required detection and prosecution, but appeared outside of the designated areas. For operators to attend to this pop-up target, manual control had to be used to drag and drop waypoints in order to navigate an UAV toward it, as the LOAs available in the system only applied to tasks being performed in the designated areas. The findings demonstrated the benefit of adaptable automation in an UAV context, whereby automation was delegated accordingly by the operator not only to better perform a tracking task, but also to deal with unexpected changes in the environment.

Building on the study by Shaw et al. (2010), Miller et al. (2011) replicated the study and found similar results with regard to tracking accuracy and time taken to deal with an unexpected event. Both studies also found that the manipulation of workload affected tracking accuracy and time to respond to the unexpected event, whereby low workload produced better tracking accuracy and faster response time to the unexpected event than did high workload. With the common assumption that automation may help mitigate high workload (Lee, 2008) it would have been interesting if both sets of authors additionally assessed when particular LOAs were shifted to and if participants used the high LOA more when it was available for use in the high workload condition.

In summary, research has suggested that automation use in UAVs offers benefits for some tasks, particularly if the lowest order of flight control is completely automated by the system. Applying LOAs at higher orders of control can also improve human-system performance, but this may be dependent on what tasks are required and when. Changing tasks and environments have focused research more recently on flexible automation use in UAVs, and while system driven adaptive automation has been explored, user driven adaptable automation requires further investigation.

1.5 The current study

While adaptive automation has been shown to improve the performance of some UAV tasks when compared to unchanging LOAs (Calhoun et al., 2012; Parasuraman et al., 2009), there is a need for research comparing the performance of UAV tasks under adaptable automation and unchanging LOAs. Furthermore, comparisons between empirical studies are made inherently difficult given the extensive range of tasks that UAVs and their operators can perform. The aim of this study was to compare the performance of operators for some UAV tasks of interest under adaptable automation, fixed (unchanging) automation, and no automation. A secondary aim was to examine the use of automation and its effect on the performance of these tasks in different area densities. Based on the available previous research (Dixon et al., 2005; Kidwell et al., 2012; Liu et al., 2009; Miller et al., 2011; Prinet et al., 2012; Ruff et al., 2002; Shaw et al., 2010; Wickens & Dixon, 2002) several hypotheses were generated:

1. Fixed automation will improve performance on tasks compared to no automation.
2. Adaptable automation will improve performance on tasks compared to no automation.
3. An accuracy over speed trade off will exist under adaptable compared to fixed automation; accuracy will improve at the expense of longer response times in adaptable compared to fixed automation (exploratory).
4. Users will rely more on fixed automation when under higher workload (exploratory).

2. Method

2.1 Participants

Forty staff and students from the Defence Science and Technology (DST) Group Edinburgh volunteered to participate in the study following an intranet daily news advertisement. The advertisement invited those interested to take part in UAV simulation research, and stated that no experience was required as all training would be provided. Those that wished to participate were required to have normal vision and colour recognition. One individual did not meet the inclusion criteria and another did not complete the study due to a technical failure in the simulation. The final data set comprised 38 participants (6 females and 32 males) with ages ranging from 24 to 53 years (M = 36.1, SD = 8.05).

2.2 Measures/Apparatus

2.2.1 Demographics

Data were collected on age, gender and gaming experience over the past four weeks using a 5-point Likert scale (1 = "Not at all", 2 = "Less than 1 hour per week", 3 = "1 to 3 hours per week", 4 = "4 to 6 hours per week", 5 = "7 or more hours per week"). The highest level on this scale typifies an experienced gamer (Strobach, Frensch, & Schubert, 2012).

2.2.2 Visual screening assessments

Visual acuity was measured using the Hanks Near Point Eye Chart (Hanks & Hanks, 2005). Normal vision is indicated by the participant reading a printed text in 5-point font size at a distance of 40 cm without errors.

Colour blindness was assessed using the Ishihara Colour Blind Test (Ishihara, 1917) which measures colour vision deficiency of congenital origin. Twenty four plates each contain a circle of dots appearing randomised in colour and size. The numerals seen on plates 1-17 are stated. For those that are unable to read numerals, plates 18-24 are used and the winding lines between the two "X"s are traced. For plates 1-15, if 13 plates are read normally this indicates normal colour vision. Nine or less plates read normally indicates colour vision deficiency.

2.2.3 Equipment – software and hardware

Virtual Battlespace 2 (VBS2) v2.02 software developed by Bohemia Interactive was used to simulate the UAV and the environment in which it operated. The software was run on an Intel I7 Workstation (Windows 7 64-bit operating system, 8 gigabytes of RAM, Nvidia GTX690 graphics card, processor clock speed of 3.50 GHz), and dual monitors (Dell 30 inch Ultrasharp 3011, resolution 2560 x 1600, 60 Hz and HP 20 inch LP2065, resolution 1600 x 1200, 60 Hz). Accessories included a HP mouse (Model M-UAE96), HP keyboard (Model KU-0316), and Microsoft Sidewinder Precision 2 joystick. To model the required

UAV functionality, both internal VBS2 scripts and external scripts written in Groovy were developed.

2.2.4 UAV simulation

All flight and navigation control of the UAV was automated. For the purpose of experimental rigour, take-off and landing were removed and the participants were only exposed to the UAV in flight. Additionally, the flight was always set at 1500 feet in altitude with a speed of 100 kilometres per hour. The UAV always flew in a circular loiter with a loiter radius of 700 metres.

Participants controlled the camera attached to the UAV, referred to as the sensor, via visual feedback on the main screen (Dell 30 inch Ultrasharp 3011) combined with the movement of the joystick. Designated buttons on the joystick controlled locking (holding the sensor at a point irrespective of UAV movement), and zooming in and out functions. Figure 2 shows the main screen and all its elements.

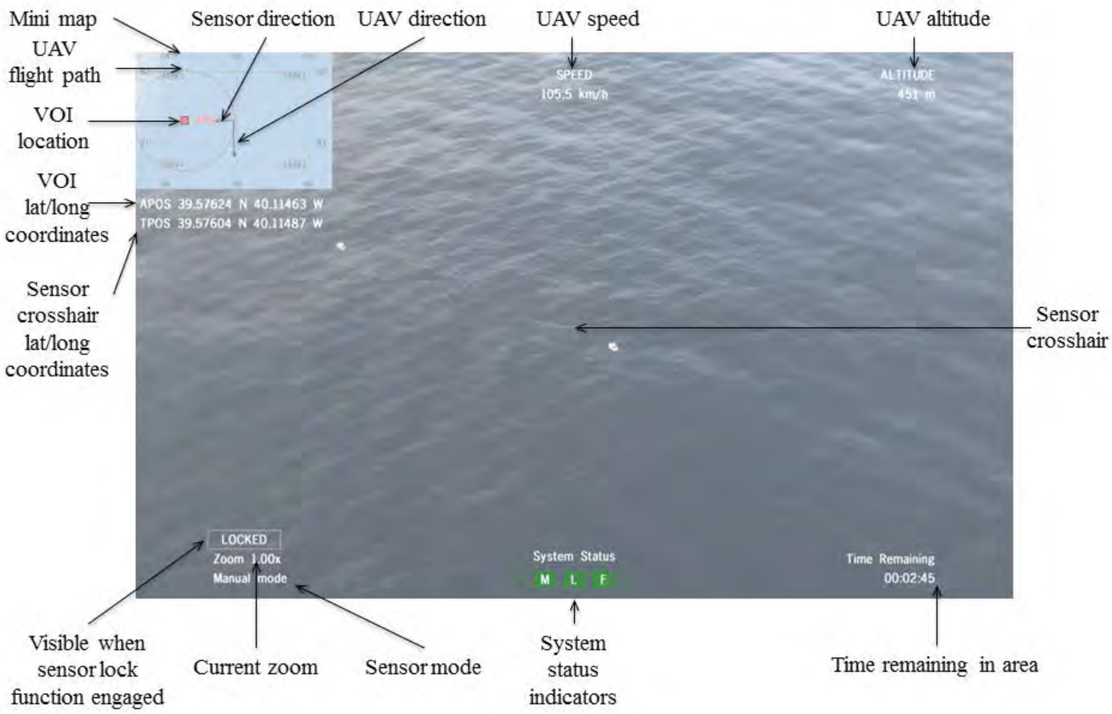

Figure 2: Visual from main screen in the study simulation.

An UAV model was created by using a VBS2 Scan Eagle model for the flight dynamics and implementing a custom sensor view. The custom sensor view was created to provide required functionality, experimental control and data capture. The sensor was attached to the UAV approximately 8 metres below the actual sensor location to avoid the sensor responding to apparent engine heat haze from the VBS2 Scan Eagle model and obstructing viewing. The sensor azimuth, pitch and zoom were set programmatically, however, the sensor roll was set by VBS2 automatically to keep the sensor view level regardless of the UAV's bank.

Implementing a custom sensor model required very frequent updates of the sensor view due to VBS2 resetting it between each display frame update. This imposed performance requirements on the VBS script execution, as missing a sensor view update between display frames would result in the sensor view flickering between two views. In support of this, VBS2 initialisation parameters were adjusted to prevent script interruption and increase the available time for script execution.

Further to the sensor model, a custom heads up display (HUD) was developed utilising VBS2 resource titles, as depicted in Figure 2. The HUD extracted data from variables stored by the relevant scripts, including scenario control, the flight model, the sensor model, and the system status model.

2.2.4.1 *Areas of investigation*

An area of investigation was defined as the surface area below the UAV within the perimeter of its flight path as indicated on the mini map (see Figure 2). Areas of investigation were designed around a subset of representative maritime environments through consultation with two subject matter experts (SMEs), and were all located within a single VBS2 scenario. When a change of area was required, scripting relocated the UAV to the new area, positioned so as to already be in the loiter flight pattern with configured bearings and directions (clockwise or anti clockwise).

Within an area of investigation was a vessel of interest (VOI) with its location and coordinates displayed (see Figure 2). The density of vessels within the area was either low (9-12 vessels in total) or high (27-36 vessels in total). The vessels for each area were programmatically created and removed at the beginning and end of flight in the area. This was to ensure the participants would not be able to inadvertently sight vessels from another area.

2.2.4.2 *Reporting task*

The participants were required to provide details about an area of investigation via an investigation report provided on the secondary screen (HP 20 inch LP2065). The report included details about the VOI as well as the total number of vessels in the area, and was designed in consultation with SMEs. The report remained constant for every area and details were entered via drop down menus under each section with selections made via the mouse, or via direct input through the keyboard.

Reports were implemented externally to VBS2 utilising a specialised programming language known as Groovy. To support coordination with VBS2, a file-based event coordination system was employed, and report data was logged to csv files. Figure 3 details the structure of the report.

Report layout	Drop down menu	Manual input	Instructions to participants
VESSEL OF INTEREST			
Class/type	Navy vessel Fishing boat Cargo vessel Pleasure craft		Choose from picture matrix.
Hull colour	White Grey Green Brown Black Red		Choose the most prominent colour of the hull of the vessel.
Has a registration number	Yes No	[ ]	Select if you see a registration number and input registration.
People visible people on board	Yes No	[ ]	Select of you see people anywhere on the vessel and input number.
Cargo sighted (boxes, barrels, crates, containers)	Yes No		Select if you see any boxes, barrels, crates or containers.
Weapons sighted	Yes No		Select if you see any weapons held by people or on board the vessel.
Suspicious activity	None Vessel overloaded with people Armed people on board		Select if below do not exist. Select if more than half of the deck is loaded with people. Select if there are people on board carrying weapons.
SUMMARY			
Total number of vessels in area		[ ]	Input total number of vessels which includes vessel of interest.

Figure 3: Investigation report structure and operator action details.

The participants had an additional picture matrix which was attached below the secondary screen and contained pictures of all the vessels used in the simulation. Each picture was columned under one of the four categories available to choose from in the drop down menu under "Class/Type".

2.2.4.3 System status task

The participants were also required to respond to changes in the system status indicators which occurred at random intervals (see Figure 2). When a system status changed from green to red, a corresponding button on the joystick base needed to be pressed in order to change the system status back to green. If the corresponding button was not pressed, the system status indicator would change back to green after 15 seconds.

A scripted system status model was developed that pre-calculated scheduled status failure times from the beginning of each task. The schedule ensured that multiple status failures could not occur concurrently, and failures occurred randomly across the allowed task time with a uniform distribution. The resource titles provided by the HUD were utilised to display each system status. Custom input handling with the script allowed for status acknowledgements from participants.

2.2.4.4 Sensor control

Three sensor control conditions were implemented:

1. Manual: The sensor required complete manipulation with the joystick from participants for all mission tasks. Participants were required to use the sensor direction with its crosshair coordinates and the VOI location with its surface coordinates to search for the VOI. Participants were also required to manipulate the sensor in order to locate and count the total number of vessels in the area.
2. Fixed: Sensor processes were completely automated. In this mode the sensor initially located the VOI and remained zoomed (x15) and locked on it for 35 seconds. The sensor then panned back to normal zoom setting (x1) and remained at a 30^{o} pitch with a 70^{o} azimuth. All remaining vessels in the area were captured in the sensor's field of view (FOV) as the UAV flew on its designated path.[1] No sensor manipulation with the joystick was permitted.
3. Adaptable: The sensor started operation in fixed mode. However, if participants chose to operate in manual mode at any time they could press a "mode" button on the joystick base that would allow this. If participants wished to change back to fixed mode, they could do so by pressing the "mode" button again. Whenever changing back to fixed mode, the sensor would always set itself at the x1 zoom level with 30^{o} pitch and 70^{o} azimuth. Participants could switch modes as often as they deemed necessary.

Table 1 outlines sensor control condition by area used in the study. Each participant took part in all conditions, and the sensor control condition order was counterbalanced across the participant pool to control for practice effects.

Table 1. Sensor control condition by area

Sensor control condition	Area density	Number of areas	System status changes per area
Manual	Low (9-12 vessels) and high (27-36 vessels)	6 (3 low followed by 3 high density)	Up to 6
Fixed	Low (9-12 vessels) and high (27-36 vessels	6 (3 low followed by 3 high density)	Up to 6
Adaptable	Low (9-12 vessels) and high (27-36 vessels	6 (3 low followed by 3 high density)	Up to 6

[1] The flight time after VOI investigation is 145 seconds, which was based on observing the UAV complete a flight lap (see 2.3.2). It should take a UAV 158 seconds to cover this distance travelling at a speed of 100 km/h However, the UAV was observed to vary its speed between 60 km/h to 120 km/h. Researchers should be aware of this variability, but we do not believe this affected our study outcomes.

2.2.4.5 Simulation metrics

For the reporting task, the performance measures were the total reporting time, which included the VOI reporting time and remaining total vessels count time, as well as the errors in the VOI detail and the total number of vessels counted. For the system status task, the performance measures included the system status response time and miss rate. Additionally, in the adaptable sensor control condition, the number of changes and time between manual and fixed modes were captured.

To support the derivation of performance measures, the data logging script periodically polled data variables for storage in csv files for subsequent analysis in Microsoft Excel. Separate data files were created for the UAV, vessels and system status due to different data fields and logging frequency requirements. All automatic data logging, with the exception of the operator reports, was coordinated from this script.

2.2.5 Subjective Workload

Self-reported workload was captured using the NASA Task Load Index (NASA-TLX) (Hart & Staveland, 1988). The participants rated their workload across six subscales from 0-100 of Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration. Higher overall scores indicated higher perceived workload.

2.2.6 Preference ranking

A sensor control condition preference ranking was collected post the experimental session from "1 – Most preferred" to "3 – Least preferred". This was created specifically for the current study to gather proportional data on which sensor control condition was most and least favoured by the participants.

2.3 Procedure

After obtaining informed consent, the participants were screened for any visual acuity and colour vision deficiencies and demographic data were obtained. All participants underwent a structured training session followed by the experimental session.

2.3.1 Training

All training was provided in a systematic fashion with all elements of the simulation and their functions explained. A training area allowed participants to practice using the elements of the simulation as well as practice their mission tasks prior to the experimental session. The training, including all function explanations and practice time, took approximately 20 minutes.

2.3.2 Experimental session

The experimental session required participants to find, investigate, and report details about the VOI in an area of investigation. Following this, the participants were required to find and count the total number of vessels in the area, but priority was always given to reporting the details about the VOI. While on any mission task, the participants were to also acknowledge any system status changes that occurred as quickly as possible. The participants were cued via a three second count down before both screens would activate and the UAV would be in flight in the area. They had a maximum of 180 seconds to complete all the tasks before the screens would go blank again.

Those taking part were instructed to complete all tasks as fast, but as accurately as possible. If they completed the tasks prior to the maximum time given, they could click “Submit” on the investigation report, which would end the time in the area and all screens would go blank. If they did not click “Submit” the time remaining in the area would count down to zero and all screens would subsequently go blank, but any information they had inputted on the investigation report would be saved by the system.

After each block of three areas of investigation, the simulation was paused and the participants were asked to fill out their ratings of current workload as indicated by the dimensions on the NASA-TLX (Hart & Staveland, 1988). This process was repeated until completion of the simulation. Participants were always told which sensor condition they would operate under, however no indication was made as to the differing area density.

After the completion of the experimental session, the participants were asked to rank their preferences of each of the sensor control conditions. The experimental session took approximately 60 minutes, thus the total participation time with training was approximately 80 minutes.

3. Results

3.1 Descriptive statistics

Participants gaming experience over the past 4 weeks ranged from 1 (Not at all) to 5 (7 or more hours per week), but were generally non-gamers (M = 2.21, SD = 1.38).

3.2 Reporting task

3.2.1 Total reporting time

A 3 (manual, fixed, and adaptable sensor control) x 2 (low and high area density) repeated measures ANOVA was used to compare total reporting times across conditions. Mauchly's test indicated the assumption of sphericity had been violated for the main effect of sensor condition ($\chi^2(2) = 9.12$, $p = .010$) and interaction effect between sensor condition and density ($\chi^2(2) = 10.15$, $p = .006$) therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ϵ = .82 and .80 respectively). Table 2 shows the descriptive statistics of total reporting times for sensor conditions and area densities overall.

Table 2. Overall total reporting times across sensor condition and area density

Sensor condition	Mean (seconds)	SE
Manual	168.43	2.05
Fixed	170.53	2.34
Adaptable	152.09	4.27
Density		
Low	160.82	2.69
High	166.55	1.12

There was a significant main effect of sensor control condition on total reporting times ($F(1.63, 60.47) = 17.01$, $p < .001$, partial $\eta^2 = .32$). Total reporting times were faster in adaptable compared to both fixed and manual sensor control ($t(37) = 4.56$, $p < .001$, $r = .60$ and $t(37) = 4.56$, $p < .001$, $r = .60$ respectively), and both were large effects. This suggested adaptable automation improved the performance of this task compared to no automation. Total reporting times did not significantly differ between manual and fixed sensor control ($t(37) = -.81$, $p = .421$, $r = .13$), which indicated fixed automation did not improve the performance of this task compared to no automation.

There was also a significant main effect of area density on total reporting times ($F(1, 37) = 15.65$, $p < .001$, partial $\eta^2 = .30$) with total reporting times faster in low compared to high density, and this was a large effect.

There was no significant interaction effect between sensor control condition and area density with regard to total reporting times ($F(1.61, 59.40) = 1.81$, $p = .306$, partial $\eta^2 = .03$).

Figure 4 shows the total reporting time against sensor condition for low and high area density.

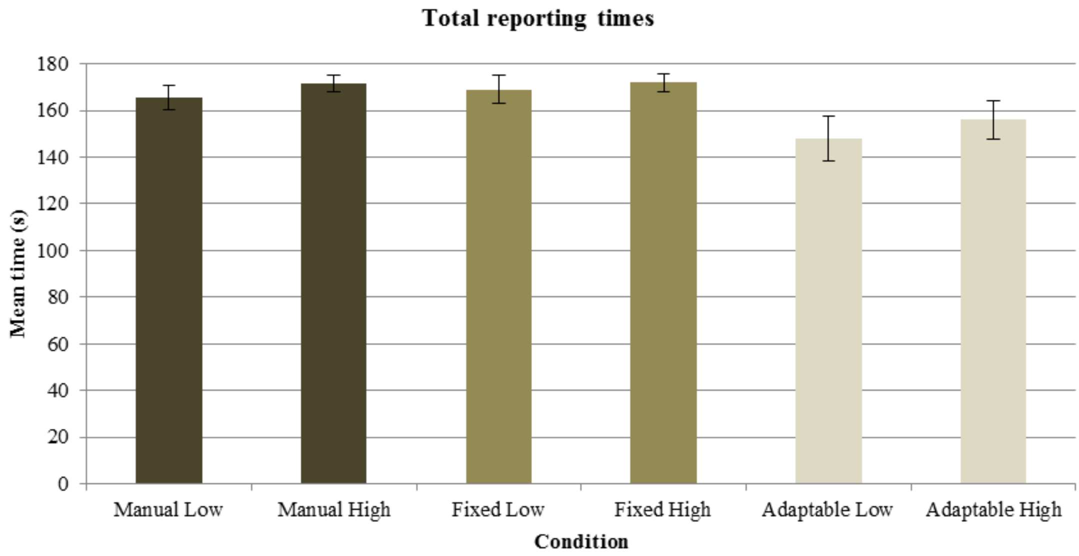

Figure 4: Total reporting time against sensor condition for low and high area density. Error bars indicate 95% confidence intervals.

3.2.2 Vessel of Interest reporting time

A 3 (manual, fixed, and adaptable sensor control) x 2 (low and high area density) repeated measures Analysis of Variance (ANOVA) was used to compare VOI reporting times across conditions. Mauchly's test indicated the assumption of sphericity had been violated for the main effect of sensor condition ($\chi^2(2) = 9.20$, $p = .010$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon = .82$). Table 3 shows the descriptive statistics of VOI reporting times for sensor conditions and area densities overall.

Table 3. Overall VOI reporting times across sensor condition and area density

Sensor condition	Mean (seconds)	SE
Manual	98.80	3.38
Fixed	39.58	1.58
Adaptable	51.99	2.84
Density		
Low	59.85	2.11
High	67.07	1.98

There was a significant main effect of sensor control condition on VOI reporting times ($F(1.63, 60.38) = 144.44$, $p < .001$, partial $\eta^2 = .80$). VOI reporting times were faster in both fixed and adaptable compared to manual sensor control ($t(37) = 17.21$, $p < .001$, $r = .94$ and

$t(37) = 10.55$, $p < .001$, $r = .87$ respectively), and both were very large effects. This indicated both fixed and adaptable automation improved the performance of this task over no automation. VOI reporting times were also faster in fixed compared to adaptable sensor control ($t(37) = -4.14$, $p < .001$, $r = .56$) and this was a large effect.

There was also a significant main effect of area density on VOI reporting times ($F(1, 37) = 9.74$, $p = .003$, partial $\eta^2 = .21$) with VOI reporting times faster in low compared to high density, and this was a large effect.

There was no significant interaction effect between sensor control condition and area density with regard to VOI reporting times ($F(2, 74) = .73$, $p = .486$, partial $\eta^2 = .02$). Figure 5 shows the VOI reporting time against sensor condition for low and high area density.

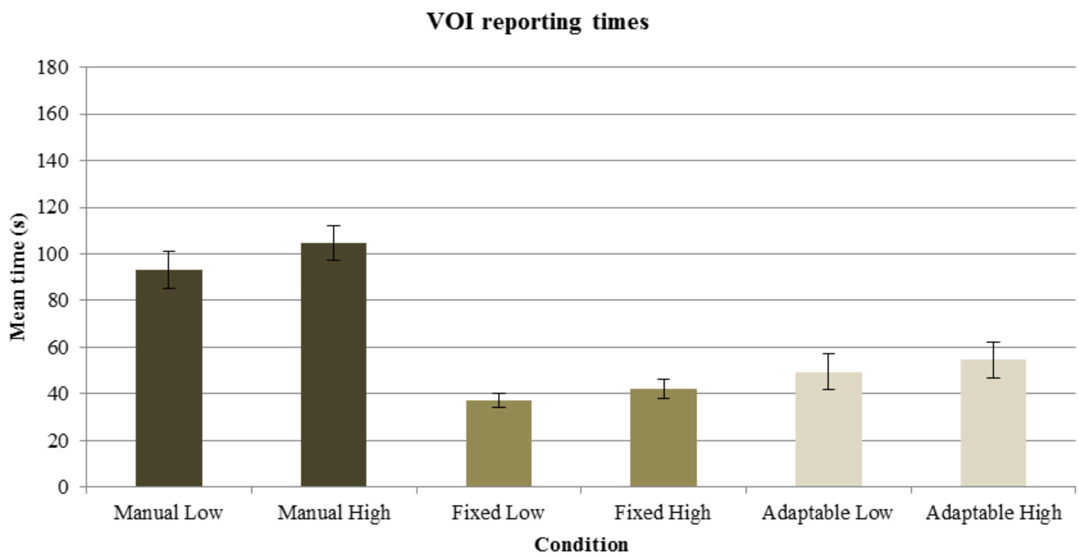

Figure 5: VOI reporting time against sensor condition for low and high area density. Error bars indicate 95% confidence intervals.

3.2.3 Total vessels count time

A 3 (manual, fixed, and adaptable sensor control) x 2 (low and high area density) repeated measures ANOVA was used to compare the total time searching and counting the total number of vessels in areas across conditions. This search time was calculated by removing the VOI reporting time from the total reporting time. Mauchly's test indicated the assumption of sphericity had been violated for the interaction between sensor condition and density ($\chi^2(2) = 12.43$, $p = .002$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon = .77$). Table 4 shows the descriptive statistics of total vessels count time for sensor conditions and area densities overall.

Table 4. Overall total vessels count times across sensor condition and area density

Sensor condition	Mean (seconds)	SE
Manual	70.08	3.05
Fixed	130.97	2.74
Adaptable	100.09	3.79
Density		
Low	101.26	2.61
High	99.49	2.52

There was a significant main effect of sensor condition on total vessel count time (F(2, 74) = 110.78, p < .001, partial η^2 = .75). Total vessel count times were faster in manual compared to both fixed and adaptable sensor control (t(37) = -15.26, p < .001, r = .93 and t(37) = -7.03, p < .001, r = 76 respectively), and both were very large effects. Total vessel count times were also faster in adaptable compared to fixed sensor control (t(37) = 7.71, p < .001, r = .79), and this was also a very large effect. It should be noted that these times are influenced by the time spent on the VOI task, which was directed to be the highest priority for participants, and the overall constraint of both tasks being completed within 180 seconds.

There was no significant main effect of density on total vessel time (F(1, 37) = .45, p = .507, partial η^2 = .01), nor any significant interaction effect between sensor condition and area density (F(1.55, 57.28) = 1.11, p = .325, partial η^2 = .03). Figure 6 shows the total vessel count times against sensor condition for low and high density.

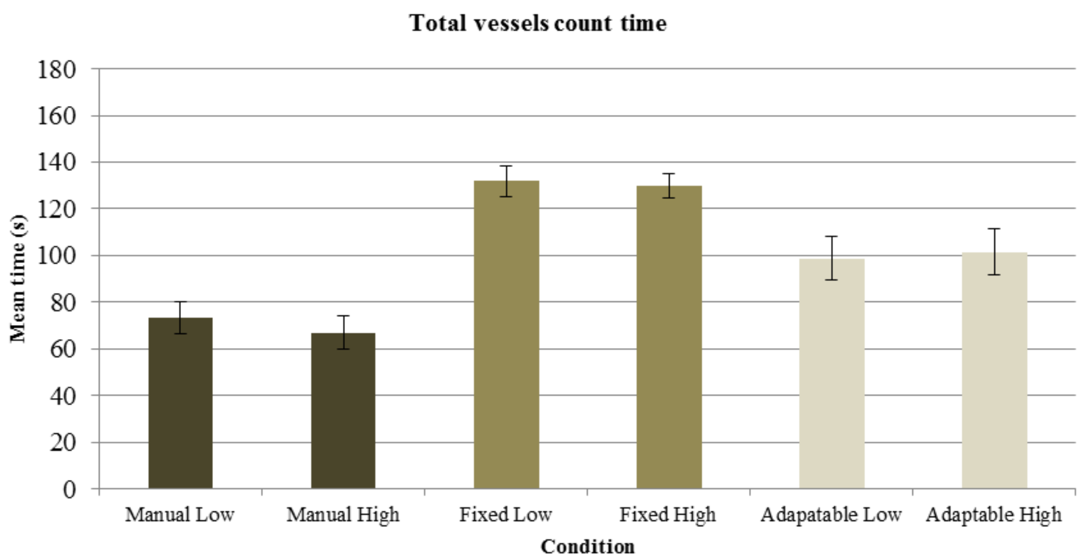

Figure 6: Total vessels count times against sensor conditions for low and high area density. Error bars indicate 95% confidence intervals.

3.2.4 VOI reporting error

A 3 (manual, fixed, and adaptable sensor control) x 2 (low and high area density) repeated measures ANOVA was used to compare VOI reporting errors across conditions.

Mauchly's test indicated the assumption of sphericity had been violated for the main effect of sensor condition ($\chi^2(2) = 22.99$, $p < .001$) and main effect of density ($\chi^2(2) = 6.82$, $p = .033$) therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ϵ = .68 and .85 respectively). Table 5 shows descriptive statistics of VOI reporting errors for sensor conditions and area densities overall. Error was calculated and termed in percentages to provide meaningful comparison between conditions.

Table 5. Overall VOI reporting error across sensor condition and area density

Sensor condition	Mean error (%)	SE
Manual	20.4	2.2
Fixed	8.6	.8
Adaptable	11.1	1.1
Density		
Low	12.6	1.1
High	14.1	1.2

There was a significant main effect of sensor control condition on VOI reporting error ($F(1.36, 50.28) = 21.45$, $p < .001$, partial $\eta^2 = .37$). VOI reporting error was greatest in manual compared to both fixed and adaptable sensor control and ($t(37) = 5.47$, $p < .001$, $r = .67$ and $t(37) = 4.14$, $p < .001$, $r = .56$ respectively), and both were large effects. Similar to VOI reporting time, this suggested fixed and adaptable automation improved the performance on this task compared to no automation. VOI reporting error did not significantly differ between fixed and adaptable sensor control ($t(37) = -2.37$, $p = .023$, $r = .36$; Bonferroni correction required $p < .017$).

There was no significant main effect of area density on VOI reporting error ($F(1, 37) = 3.11$, $p = .086$, partial $\eta^2 = .08$), nor any significant interaction effect between sensor control condition and area density ($F(2, 74) = 1.01$, $p < .368$, partial $\eta^2 = .03$). Figure 7 shows the VOI reporting error against sensor condition for low and high area density.

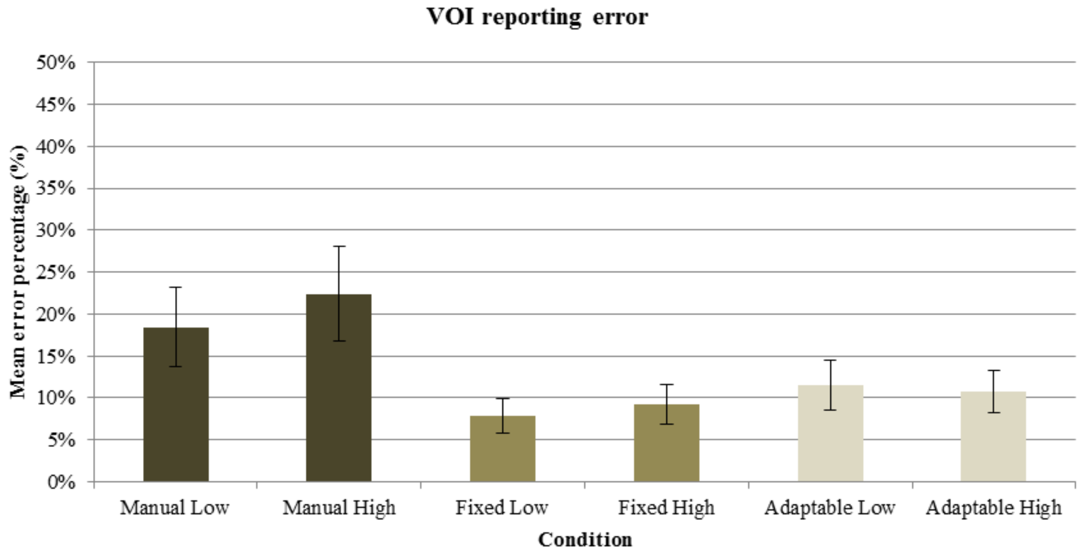

Figure 7: VOI reporting error against sensor condition for low and high area density. Error bars indicate 95% confidence intervals.

3.2.5 Total vessels count error

A 3 (manual, fixed, and adaptable sensor control) x 2 (low and high area density) repeated measures ANOVA was used to compare total vessels count errors across conditions. Table 6 shows the descriptive statistics of errors in the total number of vessels counted for sensor conditions and area densities overall. Total vessels count error was calculated and termed in percentages to provide meaningful comparison between conditions.

Table 6. Overall error in the total number of vessels in area counted across sensor condition and area density

Sensor condition	Mean error (%)	SE
Manual	34.8	3.8
Fixed	20.8	1.8
Adaptable	23.1	2.2
Density		
Low	26.9	2.1
High	25.5	2.1

There was a significant main effect of sensor control condition on error in the total number of vessels counted ($F(2, 74) = 10.32$, $p < .001$, partial $\eta^2 = .22$). The error in the total number of vessels counted was greater in manual compared to both fixed and adaptable sensor control ($t(37) = 3.77$, $p = .001$, $r = .53$ and $t(37) = 3.36$, $p = .002$, $r = .48$ respectively), and both were large effects. Similar to total reporting time, this indicated adaptable automation improved performance on this task compared to no automation. However, mixed results were apparent comparing fixed automation to no automation on this task. While fixed automation improved performance with regard to the error in the total number of vessels counted, the total time to complete the investigation report did not differ between the fixed and manual sensor control conditions (see 3.2.2). The total vessels count error did not significantly differ between fixed and adaptable sensor control ($t(37) = -.88$, $p = .384$, $r = .14$). Improved total reporting time with no increase in error on either VOI reporting or the total number of vessels counted suggested adaptable automation reduced response time without degrading accuracy compared to fixed automation.

There was no significant main effect of area density on error in the total number of vessels counted ($F(1, 37) = .69$, $p = .411$, partial $\eta^2 = .02$), however there was a significant interaction effect between sensor control condition and area density ($F(2, 74) = 7.00$, $p = .002$, partial $\eta^2 = .16$). This indicated that the sensor condition had different effects on total vessels count error depending on density. Error in the total number of vessels counted was significantly greater in manual control in high compared to low density ($t(37) = -2.29$, $p = .006$, $r = .35$), but greater in fixed control in low compared to high density ($t(37) = 2.86$, $p = .007$, $r = .43$), and both were medium to large effects. This trend was the same as the latter in adaptable control, although the difference was not significant ($t(37) = 1.11$, $p = .273$, $r = .18$). Figure 8 shows the error in the total number of vessels counted against sensor condition for low and high area density.

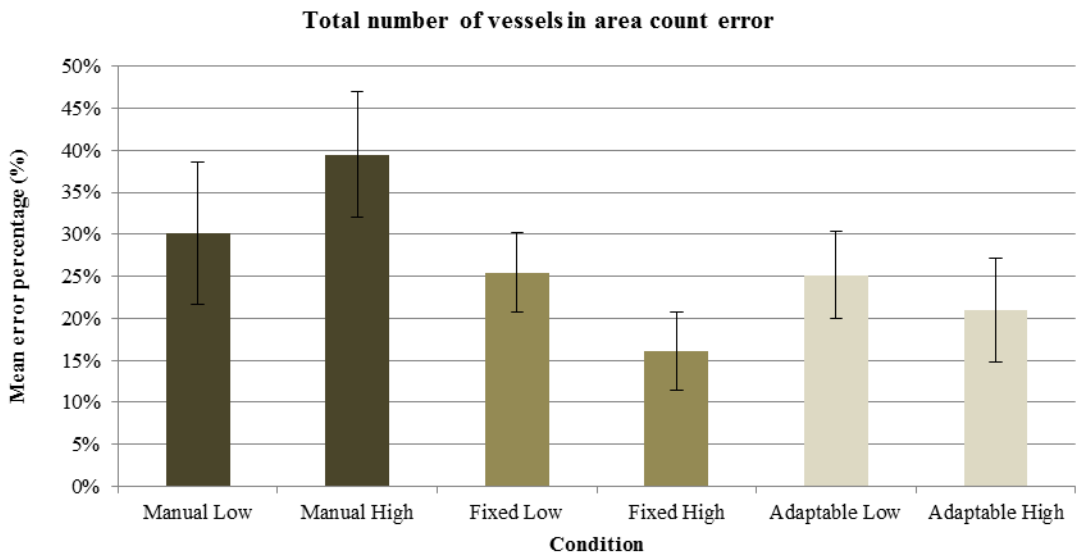

Figure 8: Error in the total number of vessels counted against sensor condition for low and high area density. Error bars indicate 95% confidence intervals.

3.2.6 System status response time

A 3 (manual, fixed, and adaptable sensor control) x 2 (low and high area density) repeated measures ANOVA was used to compare system status response times across conditions. Table 7 shows descriptive statistics of system status response times for sensor conditions and area densities overall.

Table 7. Overall system status response times across sensor condition and area density

Sensor condition	Mean (seconds)	SE
Manual	4.33	.49
Fixed	3.48	.44
Adaptable	4.37	.44
Density		
Low	4.31	.40
High	3.81	.37

There was a significant main effect of sensor control condition on system status response times ($F(2, 74) = 4.478$, $p = .015$, partial $\eta^2 = .11$). System status response times were fastest in fixed compared to both manual and adaptable sensor control ($t(37) = 2.79$, $p = .008$, $r = .42$ and $t(37) = -2.60$, $p = .013$, $r = .39$ respectively), and these were both medium to large effects, which suggested fixed automation improved performance of this task compared to no automation. Response times did not significantly differ between manual and adaptable sensor control ($t(37) = -.12$, $p = .906$, $r = .03$), which indicated adaptable automation did not improve performance on this task compared to no automation.

There was a significant main effect of area density on system status response times ($F(1, 37) = 19.445$, $p < .001$, partial $\eta^2 = .34$) with system status response times faster in high compared to low density, and this was a large effect.

There was no significant interaction effect between sensor control condition and area density with regard to system status response times ($F(2, 74) = 1.35$, $p = .266$, partial $\eta^2 = .04$). Figure 9 shows system status response time against sensor condition for low and high area density.

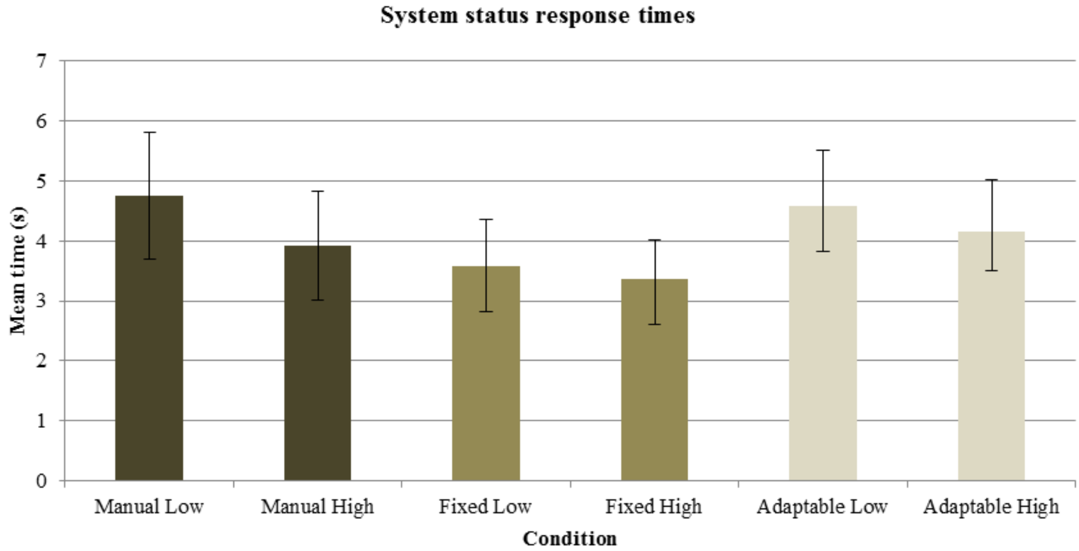

Figure 9: System status response time against sensor condition for low and high area density. Error bars indicate 95% confidence intervals.

3.2.7 System status miss rates

A 3 (manual, fixed, and adaptable sensor control) x 2 (low and high area density) repeated measures ANOVA was used to compare system status miss rates across conditions. Table 8 shows descriptive statistics of system status miss rates for sensor conditions and area densities overall. Miss rates were calculated and termed in percentages to provide meaningful comparison between conditions

Table 8. Overall system status miss rates across sensor condition and area density

Sensor condition	Mean error (%)	SE
Manual	12.9	3.2
Fixed	8.5	1.9
Adaptable	11.4	2.7
Density		
Low	12.7	2.4
High	9.2	2.2

There was no significant main effect of sensor control condition on system status miss rates ($F(2, 74) = 1.74$, $p = .183$, partial $\eta^2 = .05$), nor any significant interaction effect between sensor control condition and area density with regard to system status miss rates ($F(2, 74) = 2.23$ $p = .115$, partial $\eta^2 = .06$).

However, there was a significant main effect of area density on system status miss rate ($F(1, 37) = 14.43$, $p = .001$, partial $\eta^2 = .28$). System status miss rates were lower in high compared to low density, and this was a large effect. Figure 10 shows the system status miss rate against sensor condition for low and high area density.

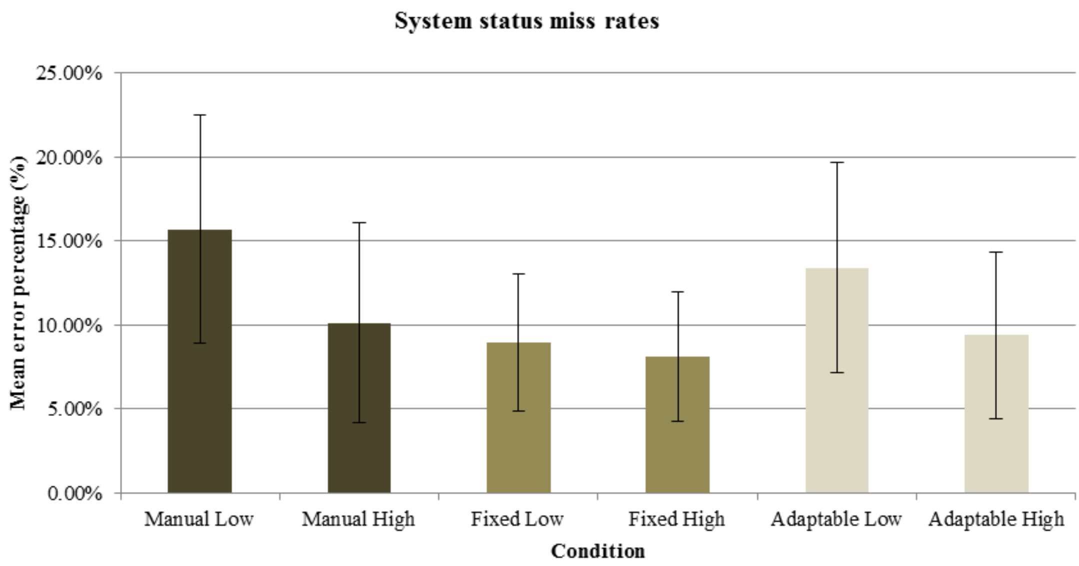

Figure 10: System status miss rate against sensor condition for low and high area density. Error bars indicate 95% confidence intervals.

3.3 Adaptable sensor control

For the adaptable sensor condition only, the number of mode changes as well as differences in time spent in the different modes was examined for low and high area density. The time spent in the different modes was then analysed separately for VOI reporting and total number of vessels reporting.

3.3.1 Mode changes

A paired t-test was used to compare the number of mode changes under adaptable sensor control between low and high area density. The number of mode changes did not significantly differ between low (M = 2.32, 95%, SE = .29) and high (M = 2.00, 95%, SE = .19) density (t (37) = 1.20, p = .237, r = .20), but this indicated the participants made use of mode changes in both low and high density.

3.3.2 Mode time

A 2 x 2 ANOVA was used to compare the amounts of time spent in manual and fixed modes under adaptable sensor control in low and high area density. Table 9 shows the descriptive statistics of amount of time spent in each mode under adaptable control and area densities overall.

Table 9. Overall time spent in each mode in the adaptable sensor control condition

Adaptable mode	Mean (seconds)	SE
Manual	89.21	4.38
Fixed	60.18	5.05
Density		
Low	73.18	2.37
High	76.21	2.08

There was a significant main effect of adaptable sensor control mode on time spent (F(1, 37) = 11.81, p = .001, partial η^2 = .24), where more time was spent in manual compared to fixed mode, and this was a large effect.

There was a significant main effect of area density on adaptable sensor control mode (F(1, 37) = 5.00, p = .031, partial η^2 = .12). Nonetheless, examining time spent in each mode was not useful when these times were combined into an overall time each for low and high density. Subsequently, this result presented no further interest for discussion.

There was no significant interaction effect between adaptable sensor control mode and area density (F(1, 37) = .68, p = .414, partial η^2 = .02). This indicated that control mode did not have different effects depending on density, and fixed automation was not relied upon more in higher workload. Figure 11 shows the times spent in the two modes for low and high area density under adaptable sensor control.

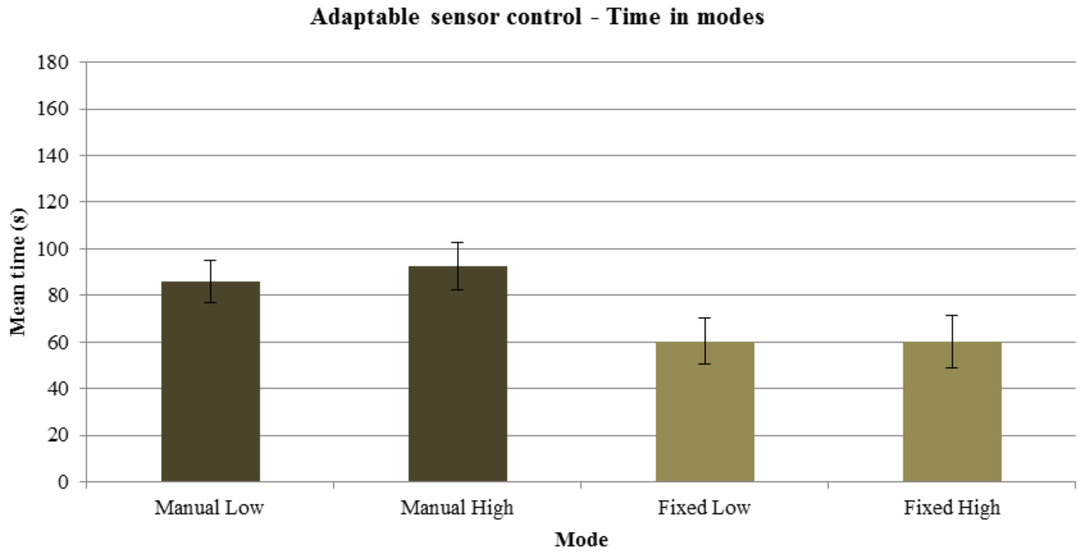

Figure 11: Time spent in each mode for low and high area density under adaptable sensor control. Error bars indicate 95% confidence intervals.

3.3.2.1 Vessel of Interest mode time

A 2 x 2 ANOVA was used to compare the amount of time spent between manual and fixed modes under adaptable sensor control during VOI reporting time. Table 10 shows the descriptive statistics of the time spent in each mode under adaptable control and area densities overall during VOI reporting.

Table 10. Overall time spent in each mode in the adaptable sensor control condition during VOI reporting

Adaptable mode	Mean (seconds)	SE
Manual	17.18	2.45
Fixed	38.88	1.04
Density		
Low	24.88	1.97
High	27.18	1.95

There was a significant main effect of adaptable sensor control on the amount of time spent between the modes during VOI reporting ($F(1, 37) = 49.53$, $p < .001$, partial $\eta^2 = .57$) where more time was spent in fixed compared to manual mode, and this was a very large effect.

There was no significant main effect of area density on amount of time spent between modes ($F(1, 37) = .70$, $p = .407$, partial $\eta^2 = .02$), and this result did not warrant further discussion (see 3.3.2). There was also no significant interaction effect between amount of time spent between modes and density $F(1, 37) = 1.38$, $p = .248$, partial $\eta^2 = .04$), which suggested that fixed automation was not relied upon more in higher workload for this task.

3.3.2.2 Total vessels mode time

A 2 x 2 ANOVA was used to compare the amount of time spent between manual and fixed modes under adaptable sensor control during searching and counting the total number of vessels in the area. Table 11 shows the descriptive statistics of the time spent in each mode in adaptable control and area densities overall during total number of vessels searching and counting.

Table 11. Overall time spent in each mode under adaptable sensor control during total number of vessels searching and counting

Adaptable mode	Mean (seconds)	SE
Manual	71.25	3.71
Fixed	24.72	4.61
Density		
Low	47.54	2.32
High	48.43	2.51

There was a significant main effect of adaptable sensor control on the amount of time spent between modes during total number of vessels searching and counting ($F(1, 37) = 38.62$, $p < .001$, partial $\eta^2 = .51$) where more time was spent in manual compared to fixed mode, and this was a very large effect.

There was no significant main effect of area density on amount of time spent between modes ($F(1, 37) = .09$, $p = .773$, partial $\eta^2 < .01$), and this result did not warrant further discussion (see 3.3.2). There was also no significant interaction effect between amount of time spent between modes and density ($F(1, 37) = .02$, $p = .902$, partial $\eta^2 < .01$), which suggested that fixed automation was not relied upon more in higher workload for this task.

3.4 Subjective workload

A 3 (manual, fixed, and adaptable sensor control) x 2 (low and high area density) repeated measures ANOVA was used to compare subjective workloads (NASA-TLX) across conditions. Table 12 shows the descriptive statistics of perceived workloads for sensor conditions and low and high area density overall.

Table 12. Overall perceived workload across sensor condition and area density

Adaptable mode	Workload score	SE
Manual	58.52	2.31
Fixed	42.27	2.58
Adaptable	52.51	2.34
Density		
Low	48.59	2.06
High	53.61	2.18

There was a significant main effect of sensor control condition on subjective workload (F(2, 74) = 30.20, p < .001, partial η^2 = .45). Subjective workload was higher under manual compared to both fixed and adaptable sensor control (t(37) = 7.17, p < .001, r = .76 and t(37) = 3.12, p = .003, r = .46 respectively), and both were large effects. Subjective workload was also higher under adaptable compared to fixed sensor control (t(37) = -4.79, p < .001, r = .62), and this was also a large effect.

There was a significant main effect of area density on subjective workload (F(1, 37) = 34.08, p < .001, partial η^2 = .48), where subjective workload was greater under high compared to low density, and this was a very large effect.

There was no significant interaction effect between sensor control condition and area density with regard to subjective workload (F(2, 74) = .02, p = .984, partial η^2 < .01). Figure 12 shows the overall workload rating against sensor condition for low and high area density.

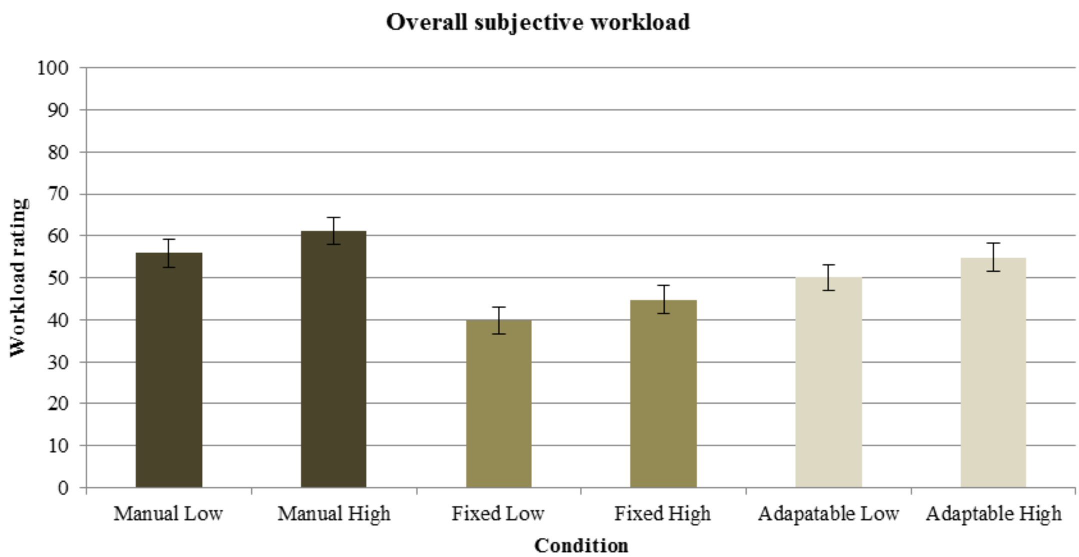

Figure 12: Overall workload rating against sensor condition for low and high area density. Error bars indicate 95% confidence intervals.

3.5 Sensor control condition preferences

Table 13 shows the distribution of preference rankings for manual, fixed, and adaptable sensor control.

Table 13. Distribution of preference rankings for manual, fixed, and adaptable sensor control

Sensor condition	1st rank (%)	2nd rank (%)	3rd rank (%)
Manual	7.9	55.3	36.8
Fixed	2.6	39.5	57.9
Adaptable	89.5	5.3	5.3

Rankings suggest that the adaptable sensor control was more preferred compared to manual or fixed sensor control. A greater proportion of participants ranked manual rather than fixed sensor control as their second preference, and fixed sensor control was the least preferred for the majority of participants.

4. Discussion

The aim of this study was to compare the performances of operators on a selection of UAV tasks under adaptable, fixed, and manual sensor control. The effect of automation on performance in different area densities was also investigated. Four hypotheses were developed to address this aim. The first hypothesis was that fixed automation would improve performance on tasks compared to no automation. This was partially supported, as it was shown that fixed sensor control improved response times and reduced error in VOI reporting compared to manual sensor control. With regard to total reporting response times, however, no difference was found/observed between fixed and manual sensor control, although there were fewer errors in reporting the total number of vessels under fixed compared to manual sensor control. Regarding the system status task, it was shown that fixed sensor control improved response times compared to manual sensor control, although no difference existed between these conditions for system status miss rates.

The second hypothesis was that adaptable automation would improve performance on tasks compared to no automation. This was also partially supported, as it was shown that adaptable control improved response times and reduced the error rates in identifying VOI and total reporting compared to manual control. However, regarding the system status task, response times and miss rates did not differ between adaptable and manual sensor control.

The third hypothesis was that an accuracy over speed trade off would exist under adaptable compared to fixed automation, where accuracy would improve at the expense of longer response times in adaptable compared to fixed automation. However, this was not supported. Although adaptable sensor control was shown to increase VOI reporting times compared to fixed sensor control, no difference in VOI error existed between conditions. Adaptable sensor control actually reduced total reporting time compared to fixed sensor control, yet no difference in error rates in reporting the total number of vessels existed between these conditions either. Regarding the system status task, response times were longer in adaptable compared to fixed sensor control, but no difference existed between these conditions for system status miss rates.

Finally, it was hypothesised that participants would rely on fixed automation more when under higher workload, but this also was not supported. Under adaptable sensor control, the time spent in fixed mode was not found to differ between low and high area density, nor was it found to differ for manual mode. Overall, participants actually spent more time in manual compared to fixed mode, but when this was broken down further it was revealed that whether more time was spent in manual or fixed mode depended on the type of reporting task being performed (see 4.4).

4.1 Fixed automation

While the tasking was different in the current study, the finding that a fixed LOA improved performance across reporting and system status tasks is in line with current research (Dixon et al., 2005; Prinet et al., 2012; Ruff et al., 2002; Wickens & Dixon, 2002). Additionally, implementing a fixed LOA was perceived as having less workload overall compared to when no automation was used. In this context, it was probably unlikely that VOI reporting would take much longer than the allotted time of 35 seconds that the sensor was locked and zoomed in on the VOI in the fixed sensor control condition. There was no option to lengthen the time the sensor was focused on the VOI, and the findings suggested that participants did complete this task accordingly, using an extra four to five seconds after the sensor had moved off the VOI to finish filling out the VOI report section, with less than 10 percent error on average. Without automated assistance, VOI reporting time increased under manual control. This result was consistent with trends found by Prinet et al. (2012), where participants also had the task demand of having to locate the VOI before reporting could commence and so the response time on that task was poor. The error in VOI reporting was also greater in manual compared to fixed sensor control, which may have been due to the lack of automated assistance adding time pressure affecting performance on this primary task (Miller, Pelican, & Goldman, 2000), or potential difficulties in manually adjusting the sensor to get a reasonable view of the VOI to obtain the required details about it. Additionally, the participants may have at times located a different vessel and reported it as the VOI, which would have increased the error in the vessel of interest reporting for this task, as an artefact of the simulation ensured details about the VOI were never completely duplicated on another vessel. These findings suggest that for the purpose of VOI reporting, a fixed LOA on sensor control to assist operators reduces reporting times and errors.

The highest priority task for participants was reporting on the VOI. Therefore, under manual sensor control the time available to count the total number of vessels was the time remaining after VOI reporting was complete, but for fixed automation this was set at 145 seconds. Most participants took close to the full time to complete both VOI reporting and vessel counting. Therefore, for manual and adaptable sensor control the vessel count time may reflect the remaining time available for this task, as opposed to the time that would have been taken had an overall time constraint not been imposed. Under manual sensor control, over half of the available time in the area was used to search and report on the VOI. Therefore, nearly all of the remaining time (70 seconds), was used to search and count the total number of vessels and subsequently finish the investigation reports. The total number of errors in counting vessels was nearly 15 per cent less under fixed compared to manual sensor control. Hence, automation improved accuracy on this task compared to no automation. However, this may be the consequence of additional time spent on this task. The proportion of time spent searching and counting the total number of vessels in areas was significantly longer under fixed than manual sensor control, with participants using 130 seconds for this part of the reporting task in the former condition, nearly double that in the latter.

The intention of the fixed time to complete both tasks was to implement a standardised approach for all sensor conditions and reflect a real world time pressure as suggested by our SMEs. However, with most participants taking close to the full time to complete both tasks, the fixed time acted as a confounding variable with regard to total vessel count times and subsequent total reporting times. In fixed sensor control, the sensor was designed to hold at a set pitch and azimuth that would allow all vessels in the area around the VOI to be captured in its FOV as the UAV flew on its designated path. This occurred over a time period of 145 seconds, although the same vessels would have begun to reappear in the FOV of the sensor just before the UAV itself completed one full flight lap.

As a result, participants in this condition had to use nearly all of the available time in order to see all of the vessels in the area. On the other hand, under manual sensor control the participants only had the time available after completing the VOI task, nearly all of which was utilised. Had we increased the time to do both tasks across conditions and given the opportunity for the fixed sensor control to capture all of the area in its FOV a second or third time, we may have seen different outcomes when comparing fixed to manual sensor control.

In this study, the fixed sensor condition was set up such that if participants noted the first vessel seen in the sensor's FOV, they could systematically count the other vessels as they appeared until they observed the first vessel again. The advantage of this set up was lost when operating under no automation. Under manual sensor control participants were forced to utilise their own search methods which, in addition to less time left to search after reporting on the VOI, was found to result in increased counting error.

Aligned with findings from Dixon et al. (2005), applying a fixed LOA to the sensor control also improved performance on the system status task compared to having no automation. In this context, reducing the task demand of sensor manipulation presumably allowed improved response times to system status changes, although the effect on miss rates was negligible.

4.2 Adaptable automation

The current study found that performance on reporting tasks improved with the ability to change between manual and fixed modes in adaptable sensor control compared to only using manual sensor control. Similar trends comparing adaptable automation to no automation have been found for other UAV tasks (Miller et al., 2011; Shaw et al., 2010)

When under adaptable control, the sensor operation started in fixed mode, which enabled participants to immediately report on the VOI without having to conduct a search for it. Consequently, reduced reporting times and error were found in the VOI reporting task under adaptable compared to manual sensor control, which supported the hypothesis proposed.

The total vessels search time under adaptable sensor control was significantly longer than that under manual control, which may have been a result of less time spent initially locating and reporting on the VOI. Providing additional support for hypothesis two, adaptable sensor control did, however, produce faster total reporting time compared to manual control. Interestingly, total reporting time was also faster for adaptable compared to fixed control, which indicates that participants must have used the mode change at various times in the adaptable control condition, otherwise total reporting times for that condition would have been similar to those for the fixed control condition (see 4.3 and 4.4).

Participants had the option of using the sensor automation or not under adaptable sensor control and executed mode changes when they felt it to be necessary. However, it was found that the option to change modes may have affected response times to system status changes such that they were slower than under fixed sensor control and in fact very similar to response times under manual control. Here lies one of the criticisms of adaptable automation. While a LOA is designed to reduce the workload of the human, the human having to designate a LOA to the system can intermittently increase workload and affect performance on tasks (Miller & Parasuraman, 2007)

4.3 Benefits of adaptable automation

Although Kidwell et al. (2012) found improved accuracy but with marginally increased response time in a change detection task for adaptable compared to adaptive automation, the proposition that we would find the same trend comparing adaptable to fixed automation across different tasks was not completely supported. Although VOI reporting time was found to be longer under adaptable compared to fixed sensor control (see 4.4), the total reporting time was actually faster under adaptable control, yet differences in error in both reporting tasks were negligible between the two conditions. In opposition to the effect observed with regard to system status responses, changing modes under adaptable sensor control did not have a detrimental effect on total reporting time in this study. This was contrary to the thought that user-delegated automation might affect performance on tasks (Miller & Parasuraman, 2007). Given total reporting time comprised the times required to perform two separate reporting tasks, interest lies in how participants utilised adaptable automation to best perform these tasks.

4.4 Adaptable automation use

It was anticipated that under adaptable control in high density areas fixed mode would be used more than manual mode, but this was not the case. We found no difference in mode use as a consequence of area density, and additionally discovered that participants spent nearly 30 seconds more in manual compared to fixed mode overall. This was a unique finding, and contradicted common thought that over-reliance and complacency might result in automation being exploited (Lee, 2008).

It was revealed that under adaptable control for the VOI reporting task, participants spent more time in fixed mode compared to manual mode. As adaptable control started in fixed mode, it was likely that participants would use the initially allotted 35 seconds with the sensor focused on the VOI, and this was evident in the findings. Only an average of three more seconds were spent in fixed mode beyond this 35 second time period, which may have been reflective of participants still inputting details on their investigation report before engaging in a mode change.

Fixed mode was not the only mode used for the VOI reporting task. Under adaptable control, participants spent an average of 17 seconds in manual mode when attending to this task. Given that under fixed control, VOI reporting error was no different than that under adaptable control, it is not entirely clear why participants might have used extra modes here. Perhaps as a result of being instructed that the VOI task was the highest priority, participants felt a need to utilise mode changing to ensure reduced error in VOI reporting. For this task, adaptable control may be considered less efficient than fixed sensor control. Speed of VOI reporting might have been traded for possible accuracy, but without any actual improvements in the latter (Miller & Parasuraman, 2007).

For the total number of vessels reporting task, more time was actually spent in manual compared to fixed mode under adaptable sensor control, with reduced reporting time overall but no increase in error compared to under fixed control. Here the ability to change the LOA of the sensor according to changing task requirement led to superior performance compared to that associated with fixed sensor control, a similar trend to those found by others (Miller et al., 2011; Parasuraman et al., 2009; Shaw et al., 2010).

4.5 Density

Previous research used a differing number of surface vehicles to count between areas in order to differentiate low and high workload (Miller et al., 2011; Shaw et al., 2010), and this design was followed in the current study. Similar trends to Miller et al. (2011) and Shaw et al. (2010) were also found in the current study whereby low density produced faster VOI and total reporting times and additionally was perceived as less workload compared to high density. However, there were also some anomalies. There was no difference between area density for VOI reporting error overall, which may have been be reflective of fixed and adaptable control already having the sensor located at the VOI initially and therefore being unaffected by the number of other vessels. On the other hand, in manual control area density was more likely to be a confounding factor as participants had to manipulate the sensor to the VOI amongst differing numbers of other vessels, yet it did not have any effect. In addition, error in the total number of vessels counted in fixed sensor control was actually higher in low compared to high area density. This suggests that changing the number of vessels in an area will not necessarily correspond to changes in overall workload. A vigilance requirement (Cummings, Mastracchio, Thornburg, & Mkrtchyan, 2013) may have inadvertently been introduced in fixed sensor control, where the constant monitoring of sparse area without being able to manipulate the sensor may have increased the error in the total number of vessels counted. Conversely, in high area density participants were constantly seeing new vessels and therefore receiving constant stimulation to count vessel numbers. A similar effect was found with regard to system status response times overall, with faster response time in high compared to low density. It may have been the case that visually scanning sparse areas while also monitoring gauges for changes could actually be more difficult than continually coming across new vessels and counting them while also noticing any changes in gauges.

4.6 Condition preferences

Participants preferred adaptable control over other sensor control conditions, which was consistent with their pattern of performance in reporting tasks across control conditions. Although fixed sensor control produced poorer performance with regard to total reporting time compared to adaptable sensor control, it did improve system status response time and was perceived as creating less workload than adaptable or manual control. Despite this, fixed control was the least preferred sensor control condition. This may have been due to participants not trusting the automation and therefore not believing it was most suitable for the task at hand (Lee, 2006).

4.7 Limitations

4.7.1 Experimental design

A potential limitation of this study was the time allowed to complete the reporting tasks. In the fixed sensor control condition, a 35 second time on the VOI and subsequent scan of the area were implemented from consultation with SMEs. However, a ceiling effect was inadvertently created whereby the majority of participants submitted the investigation report just before the finish time of an area, which was after one complete scan. If the overall time in areas had been increased and several scans of an area could have taken place, there may have been different performance effects, particularly with regard to the fixed and manual conditions for which differences in total reporting times were negligible in the current study.

Under adaptable sensor control, participants were able to switch freely between fixed and manual modes through a single mode button activation. However, when participants switched back to fixed from manual mode the sensor only moved back to the pre-programmed set angle, regardless of whether they were investigating the VOI or finding the total number of vessels in the area. Consequently, if participants accidentally pressed the mode button while the sensor was located on the VOI initially, they would need to manually manipulate the sensor if they wished to continue viewing the VOI, since pressing the mode button a second time would not take the sensor back to that location. If participants had the ability to select whether the sensor returned to the VOI or adopted the set scanning angle, this would have provided them with further control over the use of the automation, potentially improving performance and removing noise resulting from accidental mode button presses.

Parasuraman et al. (2000) suggested that LOAs might be applied along a continuum as opposed to either no automation or full automation, which was applied in the current study. The number of sensor conditions was chosen in the current study to avoid considerable complexity and the need to collect considerably more data to achieve the power required for additional analyses. An additional intermediate LOA or MBC condition, whereby the system asked participants to accept a change in automated surface searching before continuing, may have provided further insight into how adaptable automation might be used.

4.7.2 Simulation software

The VBS2 software provided the simulated environment; however, there were substantial limitations in modelling the necessary experiment functionality. Consequently, significant scripting was required involving the development of both internal VBS2 scripts and additional external scripts written in Groovy. Internal VBS2 development was limited to the scripting interface and did not involve the development of plugins, primarily due to the limited timeframe available for development and the lack of VBS2 development experience. Additionally, many initial design decisions required adjustment due to incorrect or misleading VBS2 documentation. Further time and provision of standardised software documentation may have mitigated some of these restrictions.

Existing UAV models provided by VBS2 were not adequate to meet the experiment requirements, as it was not possible to modify the user control over the sensor and difficult to adapt the provided HUD. To overcome this, an existing VBS2 UAV model was used in combination with a custom sensor view. A further complication arose from the custom sensor view responding to engine heat haze from the VBS2 Scan Eagle model, which restricted visibility and would have created a confounding variable experimentally. This was controlled through the creation of the sensor view well below the actual location of the UAV, but at the same time may have also inadvertently reduced the generalisability of the UAV system to other simulated Scan Eagle models.

Performance issues arose when modelling a large number of vessels via multiple areas located within the single VBS2 scenario. Programmatically creating and removing vessels between areas was employed to ensure participants only sighted vessels within a particular area, but this implementation also became necessary to eliminate an unacceptably slow frame rate and a resulting slowed sensor responsiveness when all vessels were present.

For the reporting task, investigation reports were initially implemented within VBS2 using a dialog control. This used VBS2 custom events to coordinate the display and submission of reports with the scenario tasking. As the modal nature of the dialog did not allow concurrent user interaction with reporting and sensor control, a second instance of VBS2 in multiplayer mode was required to run on a second computer to maintain user control of the sensor while simultaneously providing input to the report. Upon discovery that VBS2 did not propagate custom events over a multiplayer connection, the reports required re-implementing external to VBS2, utilising the custom Groovy scripts. It could have been more beneficial to implement custom Groovy scripts from the outset of the design had there been prior knowledge of some of the restrictions in creating custom events in VBS2.

4.8 Future research

The current study completely automated all flight and navigation control, and only manipulated sensor control when the UAV was in flight in the specified area to be investigated. Future research might consider having an additional change in the environment, such as the VOI moving outside of the specified area, which requires the user to set new flight paths depicted by waypoints during an experimental session. In this way, a more real world setting would be introduced in the simulation, and it would be useful to then assess how adding a task from the navigation control loop might impact performance in higher level tasks of sensor manipulation and reporting. Additionally, given that in the current study performance in the system status task deteriorated when sensor control was not completely automated, it would be practical to examine whether further impacts are resultant from additional navigational requirements.

Although the majority of previous research has focused on tasks with multiple UAV control, tasks have been varied and not directly comparable. Future research following this study might consider simply building on the number of required tasks with single UAV control. It is proposed that this is necessary to gain clearer insight into use of automation at the sensor control level, before potentially adding the complexity of more than one UAV to be managed by an operator.

To support the operator in their situational awareness, the sensor HUD included a mini map as depicted in Figure 2. The map included the location of the VOI, the flight path, location and direction of the UAV, and a direction indicator of the sensor to assist the operator with understanding where the sensor was directed. During development, the use of a dynamic length sensor indicator was explored, where the location of the indicator arrow head corresponded to centre point of the sensor view, essentially indicating the exact location the operator was viewing. Early trials of this feature, in consultation with SMEs, presented concerns that this would make the search task too easy for the operators and was subsequently removed.

An investigation into the established and researched techniques for providing the operator with an indication of the sensor view location has not been undertaken. However, the approach described above has not been seen before by the experiment team or the SMEs. Given that the dynamic length sensor indicator appeared to improve the ability of the operator to perform search tasks during pre-experiment trials, and the positive feedback from the SMEs, it may be worthwhile exploring this approach further. It may also be worth exploring the different ways of displaying a representation of the complete FOV of the sensor on the mini map in addition to the centre point indicator.

5. Conclusion

The current study has shown that automation use in an UAV context supported operators to better perform their required tasks. When automation was applied to the sensor control, it was shown to improve overall performance in reporting and system status tasks compared to when no automation was applied. However, applying an unchangeable LOA to sensor control also produced poorer performance compared to when operators had adaptable control and could manipulate the LOA of the sensor. Adaptable automation in this context better suited the need for completing different types of reporting when conducting surface search tasks, where overall reporting times were reduced without increasing error compared to fixed automation. Yet benefits were not observed across all tasks; response times and miss rates of system status changes were much the same between adaptable and manual sensor control. It is suggested that automating sensor control in UAVs will improve performance compared to when no automation is used, but an adaptable approach may provide some additional performance benefits and greater user satisfaction.

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unmanned aerial vehicles, automation, maritime operations, electrooptical sensors

19. ABSTRACT
The use of automation in uninhabited aerial vehicles (UAVs) is being explored using simulation to develop a better balance of system autonomy with human interaction for optimal human-system performance. Integrating fixed levels of automation into elements of UAV control has resulted in improved performance of some tasks, but less so when the automation does not fit appropriately to changing UAV tasks and environments. As a consequence, recent research has focused on automation that can be changed during UAV operation. The aim of this study was to compare the performance of operators for some UAV tasks of interest under automation that could be changed (adaptable), fixed automation, and no automation. A secondary aim was to examine the use of automation and its effect on the performance of these tasks in different area densities. Thirty eight participants from the Defence Science and Technology Organisation (DSTO) Edinburgh controlled the sensor of an UAV and undertook typical tasks in a maritime environment. Sensor control was manipulated to be fully automated (fixed), completely manual, or adjustable by the participant between automated and manual modes (adaptable). The results showed that fixed sensor control produced superior performance compared to manual control across tasks, but adaptable control produced additional time improvements compared to fixed control. The benefits of adaptable automation of sensor control and future research directions are discussed.