APPENDIX A—FUNCTION ALLOCATION LITERATURE REVIEW

Carl Pankok, Jr. and Ellen J. Bass

ACKNOWLEDGEMENTS

The authors would like to thank Ashley Awwad, Sherry Chappell, and Stephen Plishka for their assistance and guidance in directing the research. The authors would also like to thank Phil Smith, John Bridewell, Igor Dolgov, Ric Ferraro, and Tom Petros for their feedback and assistance with the literature review.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

EXECUTIVE SUMMARY

A systematic literature review was conducted with the objective of identifying potential unmanned aircraft system (UAS) human-automation function allocation strategies. A collection of search terms were developed representing terms related to UAS and terms related to automation, and those terms were searched in three types of literature databases: generic science and engineering databases, aviation-specific databases, and specific human factors engineering publications. Relevant literature included both UAS-specific human-automation interaction literature as well as generic human-automation interaction literature.

A taxonomy was developed to categorize the literature, encompassing topics related to function allocation strategies, measures used to assess function allocation strategies, and context/applicability of the research. A custom Microsoft Access database was developed to map the literature to the elements of the taxonomy. The literature categorizations provided a structure for a research gap analysis.

A total of 253 documents were identified as potentially relevant based on title and abstract review. Reading the documents revealed 107 documents that were relevant for the review. The research gap analysis revealed the following trends in the UAS human-automation function allocation literature:

- Information acquisition automation is underrepresented in the literature.
- Sparse work features function allocation measures, attention allocation measures, or subjective usability measures to assess automation effectiveness.
- A majority of the literature assesses automation in the en-route an aerial work phases of flight.
- A majority of the work assumes nominal environmental conditions (i.e., clear weather, no threat of controlled flight into terrain, low intruder traffic density).
- There exists sparse work assessing operation of a UAS via laptop computer, as most literature utilizes a desktop workstation containing a suite of displays.
- A majority of the study types were design/evaluation of an existing system, human-in-the-loop simulation, and literature review. Lesser-used methodologies were incident/accident analyses, computational modeling, and field tests.

1. INTRODUCTION

The use of automation is a key enabler for the integration of Unmanned Aircraft Systems (UAS) into the National Airspace (NAS). Such automation supports information acquisition; information analysis; decision and action selection; and action implementation needs (Parasuraman, Sheridan, & Wickens, 2000).

Function allocation is a process which examines a list of functions that the human-machine system needs to execute in order to achieve operational requirements, and determines whether the human, machine (i.e., automation), or some combination should implement each function. Because function allocation has key implications on safety and performance, one of the goals of the A7 project is to support the identification of recommended function allocation strategies for UAS human-machine functions. Thus the following review of the literature has been undertaken to inform the development of recommended function allocation strategies for UAS human-machine functions.

In the literature, there is currently no comprehensive taxonomy for function allocation strategies that considers all of the information processing phases: information acquisition; information analysis; decision and action selection; and action implementation automation. Thus one of the contributions of this literature review is to introduce a broad set of function allocation strategies in order to inform recommendations.

Unfortunately, there is currently no standard for assessing recommended function allocation strategies for UAS human-machine functions. Some human factors descriptions of function allocation can be too abstract or conceptual to guide specific design decisions. Sometimes only response times (RTs) and subjective measures have been used to evaluate the strategies. Thus another contribution of this work is the identification of a set of measures for comparing function allocation strategies.

Types and levels of automation (LOAs) can vary across context. Unfortunately, there is currently no standard context for identifying recommended function allocation strategies for UAS human-machine functions. Thus another contribution of this work is to identify the context to consider.

The types of studies conducted also vary in the literature from subject matter expert (SME) interview to field test. Thus this work also identifies the range of approaches used to inform recommended function allocation strategies.

The next section describes the methods used for the literature review. It is followed by the results which not only include the taxonomy and the literature review but also a research gap analysis. The main section of the document ends with a discussion. Details are included in the appendices.

2. METHODS

To conduct this literature review, we completed the following tasks: 1) identify the relevant literature, 2) develop a taxonomy to use to categorize the literature, 3) develop tools to support organizing the literature and executing the categorization, 4) categorize the literature findings, and 5) identify research gaps. This section describes how each task was conducted.

2.1 LITERATURE IDENTIFICATION

Some literature had already been identified during the writing of the project proposal and other sources had been identified by the Federal Aviation Administration (FAA). For the rest of the literature, there were two steps used to identify the relevant literature. One was to identify the sources to search and the other was to identify key words. Table 1 shows the databases searched.

Table 1. Literature search databases.

Generic Science and Engineering	Aviation-Specific	Specific Journals and Conference Proceedings
ACM Digital Library Defense Technical Information Center Engineering Village Google Scholar IEEE Xplore ScienceDirect Taylor and Francis Web of Science	FAA Technical Library NASA Technical Reports Server	Human Factors Proceedings of the Human Factors and Ergonomics Society Annual Meeting

Table 2 shows the search terms used. In the searches of the data bases, each UAS term in Table 2 was crossed was every automation term.

Table 2. Keywords for literature search.

Terms Related to UAS	Terms Related to Automation
Unmanned Aircraft System Unmanned Aerial Vehicle Remotely Piloted Vehicle	Automation Function Allocation Resource Allocation Task Allocation

While conducting the literature search, potentially relevant literature was identified based on title and abstract review. Selection for use in the review was based on review of the content of the document.

2.2 TAXONOMY DEVELOPMENT

The purpose of the taxonomy was to support coding of the identified literature. The taxonomy included three major areas:

1. Function allocation strategies,
2. Measures, and
3. Applicability of the findings.

For the function allocation strategies and the measures, an information processing paradigm based on Parasuraman et al. (2000) was applied. For each type of automation (information acquisition; information analysis; decision and action selection; and action implementation), seminal human factors engineering\human-machine systems function allocation literature was consulted and augmented with recent function allocation strategy findings. For the measures, human factors engineering and cognitive systems engineering sources were consulted. For both the strategies and the measures, literature outside of the UAS domain was consulted due to the lack of literature in the UAS area.

In the literature, findings can be very specific. For applicability of the findings, two main concepts were considered: the context of the study and the type of study. For the study context, scenario features including the type of UAS control station, remote pilot in command (RPIC) experience and demographics, RPIC task, and the environment including the airspace and traffic were considered. For the type of study, all types were considered from subject matter interview to field test.

In all cases, the taxonomy was initially developed and then updated based on the content of the literature. That is, if an attribute was missing, it was added.

2.3 SUPPORT TOOL DEVELOPMENT

EndNote X7 reference management software (Thomson Reuters Corporation, New York, NY) was used for literature organization.

The taxonomy used for the categorization is detailed in Section 3.2 of the results. A custom Microsoft Access database was implemented for the categorization. A screenshot of one of the tabs in the tool appears in Figure 1. The tool allows the user to search for a document via author name or document title. A tabbed-browsing interface is used to support categorization. When a top-level taxonomy category is selected by the analyst, a second level list box automatically populates with all subcategories falling under the selected category. For categories containing more than two levels, the lower-level list boxes automatically populate when a selection is made in the higher-level list boxes. When the analyst completes the selections in the list boxes, clicking the “Add to Database” button stores the selection(s) in a database. Below the “Add to Database” button, the author(s), title, and publication year are reported for the selected source. The category specific “Summary” list box reports any categorizations of the selected document that already exist in the database. In Figure 1, for example, the details for the methodological approach (type of study) used in the document appears.

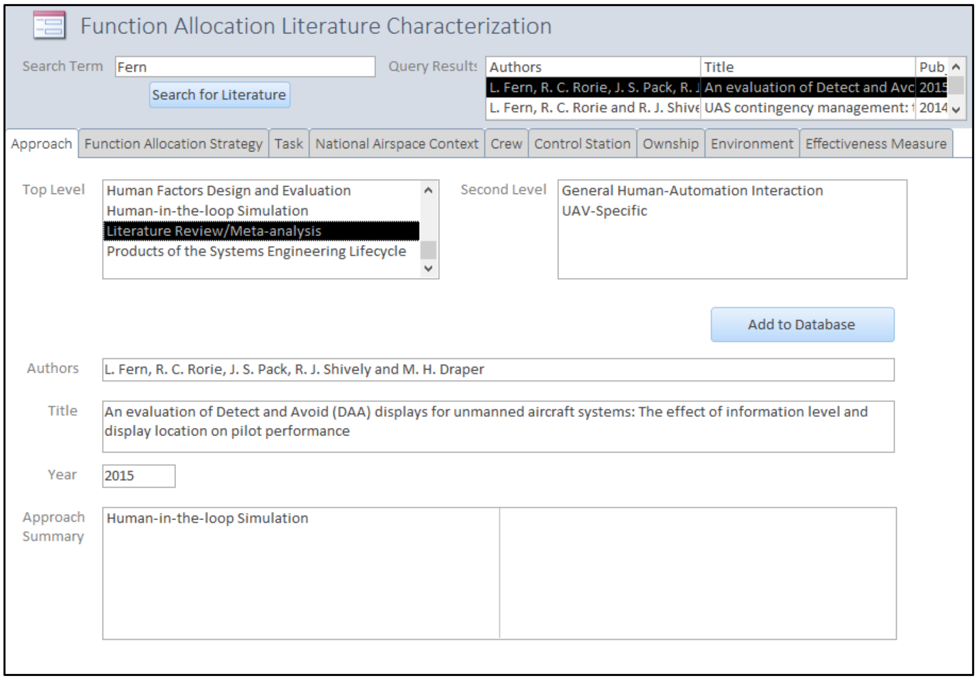

Figure 1. Microsoft Access database user interface.

2.4 LITERATURE CATEGORIZATION

Once the literature was identified and reviewed, each was categorized using the taxonomy. The findings were entered into the custom Microsoft Access database. Detailed notes were also captured in a document.

2.5 RESEARCH GAP IDENTIFICATION

Using the categorizations in the taxonomy, a series of Structured Query Language (SQL) queries were constructed to identify UAS human-automation function allocation areas lacking research. The number of documents in each categorization was revealed using the SQL “count” operator, and the percentage of the total number of categorized documents were identified as areas of future research. The queries used appear in Appendix A1.

3. RESULTS

3.1 LITERATURE REVIEWED

A total of 3,046 records were returned across the searches, and 253 were identified as potentially relevant based on the inclusion criteria. The set of documents reviewed is listed in Appendix A2.

3.2 TAXONOMY

As there was no comprehensive taxonomy to use for this literature review, one was developed that focused on function allocation strategies, measures, and applicability of the findings.

3.2.1 Function Allocation Strategy

The main purpose of this literature review was to identify the function allocation strategies suitable for UAS. As there was no existing taxonomy that addressed information acquisition, information analysis, decision and action selection, and action implementation automation, one was developed. For each stage, the purpose was to capture the different ways that the human could interact.

3.2.1.1 Information Acquisition Automation

Table 3 summarizes the information acquisition automation taxonomy. Information acquisition automation addresses sensing\presentation of data where no calculations or other forms of data manipulation are performed. On one end of the spectrum is no automation where all sensing is handled by a human such as when a visual observer may acquire information about the environment with no assistance. The category of "assisted" refers to the case where some technology collects and potentially enhances the sensing such as with night vision googles. Processed data presentation includes the situation where automation may acquire and process the sensed data for display. It also includes remote sensing. Mixed initiative data presentation includes situations where the human can control some portion of the data presentation including what data are included (such as with filtering). Because information acquisition can address a single data stream or may include data from more than one source, the taxonomy considers both the single and multiple information source cases.

Table 3. Taxonomy for information acquisition automation.

Number of Sources	**Level of Automation**	**Description**
Single Information Source	None	Human perceives information from one data source with no assistance from the automation
	Assisted	Device enhances the signal from one data source
	Processed Data Presentation	Automation presents signal processed data from one data source to the human
	Mixed Initiative Data Presentation	Automation presents signal processed data from one data source to the human to constraints specified by the human
Multiple Information Sources	None	Human perceives information from multiple data sources with no assistance from the automation
	Assisted	Device enhances the signal from multiple data sources
	Processed Data Presentation	Automation presents signal processed data from multiple data sources to the human
	Mixed Initiative Data Presentation	Automation presents signal processed data from multiple data sources to the human to constraints specified by the human

3.2.1.2 Information Analysis Automation

Information analysis automation can assist humans in making assessments by processing the acquired information. The assessment may be of the some current or future state. Information analysis automation can function in many ways such as: (1) converting raw data into an easier-to-understand form; (2) comparing sensor data to databases or models to aid in the assessment; (3) using statistical and pattern recognition techniques to highlight trends; and (4) assembling multiple sources of information into a single assessment (Bass & Pritchett, 2008). To make an assessment, a human and\or the automation may need to compare a value to a reference. The reference value itself may be fixed or situation-specific and may be under control of the human, the automation or both. Information analysis automation is often a component of an alerting system that can integrate multiple sources of information to make an assessment of the potential hazard (Bass, Ernst-Fortin, Small, & Hogans Jr, 2004; Dingus et al., 1997; Pritchett, 2001; Seagull & Sanderson, 2001). Table 4 summarizes the information analysis automation taxonomy. It separates the analysis into the assessment of a value and the determination of the reference value to use for comparison.

Table 4. Taxonomy of information analysis automation.

Level of Automation	**Description**
None	No automation
Mixed Initiative Reference Generation	The human makes the assessment; the automation makes the comparison to the reference but the human can constrain the reference
Automated Reference Generation	The human makes the assessment; the automation makes the comparison to the reference
Automated Situation Assessment	The automation makes the assessment; the human makes the comparison to the reference
Automated Situation Assessment and Reference Generation	The automation makes the assessment; the automation makes the comparison to the reference
Automated Situation Assessment and Reference Generation with Alerting	The automation makes the assessment; the automation makes the comparison to the reference and generates an alert
Automated Situation Assessment and Mixed Initiative Reference Generation	The automation makes the assessment; the automation makes the comparison to the reference but the human can constrain the reference
Automated Situation Assessment and Mixed Initiative Reference Generation with Alerting	The automation makes the assessment; the automation makes the comparison to the reference and generates an alert but the human can constrain the reference
Mixed Initiative Situation Assessment	The automation makes the assessment but the human can constrain the solution; the human makes the comparison to the reference

Mixed Initiative Situation Assessment and Automated Reference Generation	The automation makes the assessment but the human can constrain the solution; the automation makes the comparison to the reference
Mixed Initiative Situation Assessment and Automated Reference Generation with Alerting	The automation makes the assessment but the human can constrain the solution; the automation makes the comparison to the reference and generates an alert
Mixed Initiative Situation Assessment and Reference Generation	The automation makes the assessment but the human can constrain the solution; the automation makes the comparison to the reference but the human can constrain the reference
Mixed Initiative Situation Assessment and Reference Generation with Alerting	The automation makes the assessment but the human can constrain the solution; the automation makes the comparison to the reference and generates an alert but the human can constrain the reference

3.2.1.3 Decision and Action Selection Automation

Decision and action selection automation addresses generating and selecting among a set of action alternatives. For function allocation we use a modified version of the Sheridan and Verplank (1978) taxonomy where the mixed initiative interaction is explicit. Table 5 summarizes the decision and action selection automation.

Table 5. Taxonomy of decision and action selection automation.

Level of Automation	Description
None	Human generates potential decision/action options and chooses an option
Assisted Option Generation	Human generates potential decision/action options subject to constraints set by the automation
Automated Option Generation	Automation generates potential decision/action options; human chooses an option
Filtered Option Generation	Automation generates a subset of the potential decision/action options; human chooses an option
Automated Option Ordering	Automation generates potential decision/action options and ranks them; human chooses an option
Mixed Initiative Option Generation	Automation generates potential decision/action options subject to constraints set by the human; human chooses an option
Management by Consent	Automation generates potential decision/action options and chooses an option; operator accepts or rejects option
Management by Exception	Automation generates potential decision/action options and chooses an option; human has a window to reject option before it is selected
Mixed Initiative Decision Selection	Automation generates potential decision/action options subject to constraints set by the human; automation chooses an option

Fully Automated Decision Selection	Automation generates potential decision/action options and chooses an option without human involvement

3.2.1.4 Action Implementation Automation

The action implementation stage of processing includes which agent implements the action (human vs. automation), as well as the level of feedback provided by the automation to a human if the automation implements the action. Table 6 summarizes the action implementation automation.

Table 6. Taxonomy of action implementation automation.

Level of Automation	**Description**
None	Human implements action
Compulsory Feedback	Automation implements action and necessarily informs human
Feedback by Request	Automation implements action and informs the human if requested by the operator
Feedback by Design	Automation implements action and informs the human only if it decides to inform the human
No Feedback	Automation implements action and does not inform the human

3.2.1.5 Automation Reliability

Imperfect automation has great influence on operator behavior, as automation that generates incorrect suggestions or actions can lead to operator distrust in the automation, increasing workload and decreasing system performance. Generally, automation that is less than 70% reliable has been reported to be worse for system performance than no automation at all (Onnasch, 2015). Dixon and Wickens (2006) and Wickens, Dixon, and Johnson (2006) have shown the differential effects of false-alarm-prone and miss-prone automation on human performance. Since operator behavior can be altered by imperfect automation, the taxonomy accounts for automation reliability. The ten automation reliability categories reflect the percentage of time the automation provides a correct decision, action, or alert; 0%-10%, 10%-20%, 20%-30%, etc.

3.2.2 Measures

Researchers use different measures to evaluate function allocation strategies and to evaluate human performance with UAS.

3.2.2.1 Function Allocation Measures

An analysis of function allocation must necessarily consider the metrics to be used to measure performance and the function allocation strategies need to be compared using those metrics. As described in Pritchett, Kim, and Feigh (2014), measuring function allocation strategies can be evaluated using eight categories: workload/taskload arising from all sources, mismatches between responsibility and authority, stability of the humans' work environment, coherency of the function allocation, interruptions, automation boundary conditions, system cost and performance, and humans' ability to adapt to context.

Taskload metrics include immediate workload or taskload relative to thresholds, as well as considering workload spikes or longer-duration periods of workload saturation. Methods to assess the workload associated with a given function allocation can include subjective ratings in multiple dimensions, such as measuring via psychophysical scaling (Dixon, Wickens, & Chang, 2005) and multidimensional rating systems (Hart & Staveland, 1988; Potter & Bressler, 1989). Mismatches between responsibility and authority can be quantified statically by the number of functions with mismatches between responsibility and authority, and dynamically by the number and combined duration of the induced monitoring actions (Lee & Bass, 2015). Stability of the work environment can be measured by the extent to which the function allocation allows human team members to predict (and potentially plan for) upcoming actions. A particular function allocation strategy may distribute functions in a way such that one agent will trigger the requirement for another to act. Thus, a person's ability to predict his or her activities can have great value for system stability; although some unpredictability may be inherent to the work environment, a function allocation should not limit the person's ability to predict and schedule his or her own activities. Coherency addresses the interleaving of functions assigned to humans and automation that creates obstacles to each agent's being able to perform assigned functions. An allocation may require significant coordination or idling as one waits on another, or when workload may accumulate. Interruptions are another important type of measure, particularly when unexpected situations require immediate action or when one operator is interrupting another. Function allocations should not divide functions between agents such that they create the need for interruptions. Another metric, automation boundary conditions, recognizes when the immediate situation violates the fixed set of boundary conditions in which the automation is operable and, thus, is appropriate to use. Cost is dependent on the domain objectives such as fuel burn. Adaptation addresses situations where the human's behavior does not meet what is expected by the function allocation.

3.2.2.2 Human-automation Interaction Measures

In their model for types and levels of human interaction with automation, Parasuraman et al. (2000) identify four primary evaluative criteria for automation design.

The first, mental workload, can be reduced with well-designed automation. Reduced mental workload has generally been associated with better operator performance, but workload that is too low can induce boredom. Workload is typically measured via a unidimensional Likert scale, a multidimensional scale, performance in a secondary task, and/or via objective physiological measures (Wickens, Lee, Liu, & Gordon Becker, 2003).

Situation awareness (SA) is defined as the perception of cues, the comprehension of those cues as they relate to system status, and the projection of future system states (Endsley, 1995b). SA can be measured via objective ratings scales, although they may not yield a reliable measure of SA since operators do not know what they do not know. Objective measures such as the Situation Awareness Global Assessment Technique may be better indicators of operator SA (Endsley, 1995a). Mental workload reflects the degree of saturation of the operator's cognitive resources. In the design of automation, there is generally an expected tradeoff between SA and mental workload (Onnasch, Wickens, Li, & Manzey, 2014); system designers strive to design a LOA that facilitates operator SA while simultaneously minimizing workload.

Complacency, characterized by over-trust in automation, can be most detrimental when automation is highly but not perfectly reliable (Parasuraman et al., 2000).

When operators use high LOAs over extended periods of time, skill degradation can occur, making it difficult for the operator to effectively intervene in the case of an automation breakdown.

Regarding trust, operator decisions to use automation is highly dependent on trust; if automation engenders a low level of trust, the operator may choose not to use it (Parasuraman & Riley, 1997).

Reliance on automation, particularly over-reliance, can result from decision biases or failure to properly monitor automation. Reliance is characterized by inability of the operator to ensure the automation is performing properly, and can result from excessively high workload and/or automation with inconsistent reliability (Parasuraman & Riley, 1997).

Finally, utilization is a measure of the percentage of time the operator is engaged in a task, and is a measure typically output by computational models (Cummings, Marquez, & Visser, 2007).

3.2.2.3 Mission Performance Measures

Differing function allocation strategies for UAS will necessarily have effects on aviation-specific measures of effectiveness. This review includes a collection of commonly-used measures to assess aviation efficiency and performance. Fuel consumption is a measure of the fuel used during a portion of a flight, and conflict resolution maneuver quality is a measure of the efficiency of a resolution maneuver. Measures of maneuver efficiency include whether or not the maneuver effectively resolves an impending conflict, and the angle of the maneuver off of the cleared path (a smaller angle reflects a more efficient maneuver). Delay is a measure of the elapsed time between the expected time of arrival and the actual time of arrival. Compliance reflects the percentage of time a UAS operator performs the maneuver given to him/her, either by Air Traffic Control (ATC) or automation such as Traffic Collision Avoidance System (TCAS). Flight path error is a measure of the distance away from the cleared path (either horizontally or vertically) of a UAS, while speed error measures the difference between actual speed and cleared speed. Finally, the amount of training required for an operator/system to meet a minimum performance criterion is included as a measure of the function allocation, as well as landing-performance measures such as nose position (e.g., high or low), lateral velocity, distance off centerline, vertical velocity, and glideslope error (Schreiber, Lyon, Martin, & Confer, 2002).

3.2.2.4 Detection/Judgment Measures

3.2.2.4.1 Signal Detection Theory

The probability-based signal detection theory paradigm has been used to model the detection of an even in the presence of an evidence variable, “X”, and noise (Green & Swets, 1989). The human judge has the task of differentiating the signal (often in the presence of noise) from the noise alone. There is a threshold or cutoff above which the stimulus or evidence variable must be for detection to occur. The signal detection theory model assumes that the person has such a cutoff value, C_h, a bias measure. When the properties of X exceed C_h, the person would then assert that the signal is present. The combinations of the states of the world (signal or noise only) and the two possible responses ("yes", there is a signal or "no", there is no signal) create four classes of joint events: two are correct responses (hit and correct rejection) and two are errors (false alarm and miss) From the four possibilities, four probabilities are calculable:

- P(H): Probability of a hit (number of hits/number of signal events)
- P(FA): Probability of a false alarm (number of false alarms/number of noise only events)
- P(M): Probability of a miss (number of misses/number of signal events)
- P(CR): Probability of a correction rejection (number of correct rejections/number of noise only events)

Signal Detection Theory uses two parameters to model detection (sensitivity and response criterion or bias) (Green & Swets, 1989). Sensitivity is an index of the human's ability to distinguish the signal from the noise. Response bias is the human's tendency to respond positively or negatively as a function of the four outcomes and the likelihood of a signal being present. With the assumptions of normality and of equal variance for the two distributions, the index of sensitivity is calculated as the distance between the means of the signal and the noise scaled to the standard deviation of the noise distribution. The response criterion is the likelihood ratio that an effect of the cutoff criterion is due to signal plus noise as opposed to noise alone.

3.2.2.4.2 Double System Lens Model

Judgment analysis uses the lens model (Brunswik, 1956) which has been applied to describe how people make judgments about their environments. A double system design is a model that considers the judgment process and the task conditions and computes judgment accuracy with respect to an objective criterion or other standard. This commonly used form of the Lens Model provides symmetric models of both the human judge and the environment. The model describes the human judge, the task environment, and the interrelationships between these two entities. The task environment is modeled in terms of the cues available and the environmental criterion to be judged. Cues and the criterion are related by statistical correlations known as ecological validities (e.g., ecological validity of a cue measures how well it specifies the true state of the environmental criterion to be judged). Correlations reflect environmental relationships between the cues and the criterion within the task environment.

A judge uses the cue values to render a judgment about the environmental criterion. Over cases, one will find various correlations between the cue values and human judgments, and these are known as cue utilizations, the r_s values. The particular pattern of cue utilizations exhibited by a human judge determines the cognitive judgment strategy. Achievement will be maximized when the pattern of cue utilizations (in the cognitive judgment strategy) mimics the pattern of ecological validities (in the task environment). Achievement, r_a, is measured by correlating the criterion, Ye, to the judgments, Ys. The lens model structure yields the lens model equation (Hursch, Hammond, & Hursch, 1964; Tucker, 1964):

$$r_a = G R_e R_s + C\sqrt{1 - R_e^2}\sqrt{1 - R_s^2}$$

where:
r_a = Achievement
G = Linear Knowledge
R_e = Environmental Predictability
R_s = Cognitive Control
C = Nonlinear Knowledge

As a correlation, the highest achievement value is one. If achievement is less than one, it can be decomposed via the lens model equation in order to understand why judgment performance is not perfect. The first part of the equation is the product of Environmental Predictability (R_e), Cognitive Control (R_s), and Linear Knowledge (G).

Environmental Predictability, R_e, measures a limit to judgment performance based on the predictability of the environment. Environmental predictability is based on task factors (e.g., task specific features, cue reliabilities) and is calculated as the multiple correlation of the environmental linear regression model (regressing the criterion on the cue values).

The consistency with which a judge can execute his or her strategy is captured by cognitive control. Even though a judge might have perfect task knowledge, performance can be limited by the judge's inability to apply that knowledge in a controlled and consistent fashion over time or cases (Bisantz et al., 2000). Importantly, it is possible to measure the separate, independent contributions of task knowledge and cognitive control as performance limiting factors using judgment analysis (for a review, see the cognitive information related results in Balzer, Doherty, and O'Connor (1989)). Cognitive control is calculated by regressing human judgments on the cue values. R_s is the resulting multiple correlation obtained as a result of this regression analysis.

Linear Knowledge (G) is the correlation between the predictions of the two (environmental and cognitive) regression models. In judgment analysis, the adequacy of a judgment strategy (in terms of beta weights in the linear regression model of the strategy) is the linear knowledge. G indicates the level of judgment performance if the environment and the human judge were completely linearly predictable (where a G of 1 indicates that the judge has perfect linear knowledge of the environment and a G value of 0 indicates that the judge has no linear knowledge of the environment). Even highly experienced domain experts can vary in terms of whether their judgment strategy mirrors the beta weights describing the task environmental structure. Limitations in linear knowledge are associated with a failure to correctly understand the reliabilities of the various judgment cues (for a review, see the task information related results in Balzer et al. (1989)).

The second term in the lens model equation deals with any nonlinear effects not captured by the purely linear effects represented in the first term. C is the "Nonlinear Knowledge" (a measure of any correlation between the human's judgments and the environmental criterion that cannot be explained linearly). In judgment analysis, nonlinear knowledge, or C, is calculated as the correlation between the residuals of the environmental linear regression model and the cognitive linear regression model. Its role is to identify if the judge is capturing non-linear components in the environment that are not captured in a linear model. A low value for C cannot, however, be interpreted as an actual lack of unmodeled response variance as it may indicate substantial but unrelated and unmodeled variance (Cooksey, 1996).

3.2.2.4.3 Skill Score

Stewart and Colleagues (Stewart, 1990; Stewart & Lusk, 1994) expanded the Lens Model to include two additional parameters. The expansion is based on Murphy's skill score (SS), a relative measure of judgment goodness. Murphy (1988) considered the "distance" between data sets to conceptualize judgment goodness. Mean Square Error (MSE), a measure of the squared Euclidean distance between two data sets (Cooksey, 1996), defines the concept of distance:

$$MSE_Y = (1/n)\ \Sigma(Y_{si} - Y_{ei})^2$$

Several different decompositions of MSE have been suggested in the literature (Cooksey, 1996; Lee & Yates, 1992). In some decompositions, one judgment system serves as a reference against which the other judgment system is compared. To measure the goodness of the standard, Stewart (1990) suggested using a constant judgment based on the average value of the situational states being judged:

$$MSE_R = (1/n)\ \Sigma(Y_{ei} - Y_{ei})^2$$

To derive the measure of skill requires the ratio between the MSE of the operator's judgment and the MSE of the standard. This ratio is then subtracted from unity to create the skill score (SS):

$$SS = 1 - [MSE_Y / MSE_R]$$

Murphy (1988) developed the SS to enable the MSE to be decomposed. SS can be decomposed into three components: shape, scale error, and magnitude:

$$SS = (r_a)^2 - [r_a - (\sigma_{Ys}/\sigma_{Ye})]^2 - [(Y_s - Y_e)/\sigma_{Ye}]^2$$

The shape component, also called *Resolution*, measures the ability to discriminate between the occurrence and nonoccurrence of situational events (Stewart & Lusk, 1994). SS reduces to a measure of shape (correlation) only when the remaining two components (scale error and magnitude error) are equal to zero (Murphy, 1988). It is calculated in the same manner as the Lens model achievement.

A regression bias manifests as a general tendency to produce judgments on an interval that is larger than found in the true situation (Lee & Yates, 1992; Stewart & Lusk, 1994). The judge must adjust the variability of his or her judgments to be proportional to the variability of the environmental criterion in order to account for regression toward the mean. Making judgments with either too little or too great a range or variation results in a regression bias. The scale error component, also called *Conditional Bias* or *Regression Bias*, measures whether the operator has appropriately scaled judgmental variability to situational variability. It is zero when the slope of the regression line predicting the observed events from the operator's judgments is 1.0 (Stewart & Lusk, 1994).

Consistently erring either on the side of caution or risk results in a base rate bias (Stewart, 1990). The mean value of human judgments should be equal to the mean value of the environmental criterion (i.e. the objective base rate) or else a base rate bias is evident. The magnitude error component, also called *Unconditional Bias* or *Base Rate Bias* measures the overall (unconditional) bias in the operator's judgments, thus diagnosing a tendency to over- or underestimate the judged situation. This bias equals zero when the mean of the operator's judgments equals the mean of the judged states (i.e., the objective base rate).

3.2.2.5 Control Measures

Control measures, such as RT, target tracking performance, and Fitts' (1954) Law, can be sensitive to different function allocation strategies and automation manipulations.

3.2.2.6 Attention Allocation Measures

Operating a UAS requires a high level of visual attention, as sensory information is lost due to the operator being remotely located from the vehicle (Williams, 2008). Since most information is perceived visually, measuring pilot attention can be an effective way to assess various function allocation strategies, including whether the pilot is devoting sufficient time to essential information, or as a psychophysical objective measure of workload.

Fixation frequency is defined as the proportion of fixations devoted to one display or area of interest, where a fixation is defined as a time in which gaze remains "fixed" for more than 100 ms (Holmqvist et al., 2011).

Glance duration is defined as the total time the operator's gaze remains in an area of interest, accounting for both fixations and saccades (where a saccade is defined as the fast movement of gaze between fixations).

Fixation duration measures the length of a fixation, and total viewing time is a measure of the sum of the entire time over a time period in which the participant is looking at an area of interest.

3.2.2.7 Usability Measures

Usability measures are used to assess how easy user interfaces are to use. The word "usability" also refers to methods for improving ease-of-use during the design process (Nielsen, 1993). With UAS, usability measures may be collected using subjective surveys or questionnaires given to RPICs or SMEs with respect to a control device, display information, alerting functionality, or other UAS features.

3.2.3 Context of the Study

The context of the study includes the situation under which the study was conducted.

3.2.3.1 Task

This portion of the taxonomy considers the task work. Task work is considered by flight phase, general function, mission, and flight event (nominal and failure). Phase of flight includes the traditional aviation flight phases plus it includes the specific mission which, due to its complexity, is specified separately.

The phases of flight include:

- Flight Planning
- Engine Start
- Taxi
- Takeoff
- Departure
- En Route
- Aerial Work/Mission
- Descent
- Approach
- Landing

The generic functions include (Hobbs & Lyall, 2015):

1. Manage
    a. Plan for Normal Conditions
    b. Plan for Non-normal Conditions
    c. Make Decisions in Normal Conditions
    d. Recognize and Respond to Non-normal Conditions
    e. Transfer Control
2. Aviate
    a. Monitor and Control Aircraft Systems (Including Automation)
    b. Monitor Consumable Resources
    c. Monitor and Configure Control Station
    d. Maneuver Aircraft to Avoid Collision
    e. Monitor and Control Status of Control Links
3. Navigate
    a. Control and Monitor Aircraft Location and Flight Path
    b. Remain Clear of Terrain, Airspace Boundaries, and Weather
    c. Self-separate from Other Aircraft
    d. Ensure Lost Link Procedure Remains Appropriate
    e. Terminate Flight
4. Communicate
    a. Air Traffic Control
        i. Ground Control
        ii. Local Control
        iii. Terminal Radar Approach Control
        iv. Air Route Traffic Control Center
    b. Pilots of Other Aircraft
    c. Crew Members
    d. Ancillary Services (e.g., weather)
5. Mission

The mission is the specific purpose for the flight (Nehme, Crandall, & Cummings, 2007; RTCA Inc., 2010):

1. Military
    a. Reconnaissance/Surveillance
    b. Tactical Strike
    c. Communication Relay
    d. Signal Intelligence
    e. Maritime Patrol
    f. Penetrating Strike
    g. Suppression of Enemy Air Defenses (SEAD)
    h. Aerial Refueling
    i. Counter Air
    j. Airlift
    k. Target Search
    l. Target Identification
2. Civil
    a. Atmospheric Research
    b. Border Patrol
    c. Disaster Response
    d. Hurricane Measurement and Tracking
    e. Forest Fire Monitoring and Support
    f. Search and Rescue
    g. Maritime Surveillance
    h. Law Enforcement
    i. Humanitarian Aid
    j. Aerial Imaging and Mapping
    k. Drug Surveillance and Interdiction
    l. Monitor and Inspect Critical Infrastructure
    m. Natural Hazard Monitoring
    n. Airborne Pollution Observation and Tracking
    o. Chemicals and Petroleum Spill Monitoring
    p. Communications Relay
    q. Traffic Monitoring
    r. Port Security
3. Commercial
    a. Crop Monitoring
    b. Fish Spotting
    c. Remote Imaging and Mapping
    d. Utility Inspections
    e. Mining Exploration
    f. Agricultural Applications
    g. Communication Relay
    h. Petroleum Spill Monitoring
    i. Site Security
    j. Broadcast Services
    k. News Media Support
    l. Filming
    m. Real Estate Photos

n. Aerial Advertising
o. Cargo

3.2.3.2 Environment

This portion of the taxonomy accounts for the external environment in which the UAS operated (Federal Aviation Administration, 2014):

1. Atmospheric
    a. Wind
    b. Visibility
    c. Weather
    d. Sky Conditions
    e. Air Temperature
    f. Pressure
    g. Precipitation
    h. Turbulence
    i. Ice
2. Lighting
    a. Day
    b. Night
3. Intruder Traffic
    a. Vehicle Type
        i. Airship
        ii. Glider
        iii. Helicopter
        iv. Manned Powered Aircraft
        v. Unmanned Powered Aircraft
    b. Position Broadcast Equipment
        i. Radar-Based
        ii. Satellite-Based
        iii. ADS-B
        iv. Mixed
        v. None
    c. Density
        i. None
        ii. Unspecified
        iii. <5 Intruder Encounters
        iv. 5-10 Intruder Encounters
        v. >10 Intruder Encounters
4. Geography
    a. Restricted Airspace
    b. Buildings
    c. Natural Obstacle
    d. No Obstacles
    e. Other Obstacle

3.2.3.3 National Airspace Context

The national airspace context portion of the taxonomy includes the airspace class that the UAS operated in (including oceanic airspace), the surface portion of the flight, and the flight rules associated with UAS operation in the literature. The surface subcategory captured where the UAS flight originated and returned to, such as an airport, a non-airport (e.g., automated launcher or net retrieval system), and watercraft (e.g., an aircraft carrier). The details for this part of the taxonomy include:

1. Airspace
    a. Class A
    b. Class B
    c. Class C
    d. Class D
    e. Class E Below A
    f. Class E Above A
    g. Class G
2. Oceanic
3. Surface
    a. Airport (Ramp, Taxiway, Runway)
    b. Non-airport Ground
    c. Watercraft
4. Flight Rules
    a. Visual Flight Rules
    b. Instrument Flight Rules

3.2.3.4 Participants/Crew

This portion of the taxonomy addresses the participants and their roles as well as critical demographics. Pilot-in-command was defined as the operator responsible for control of the aircraft, generally located in a ground control station (GCS). Schreiber et al. (2002) report differences in required training time for Predator UAS RPICs with prior UAS experience, RPICs with prior manned aircraft flying experience, and RPICs with no prior flying experience in manned or unmanned operations. Therefore, the taxonomy accounts for prior experience of the pilot(s)-in-command used in the study (prior unmanned experience, manned experience, mixed experience, no experience, or unspecified). Some systems require takeoff and landing by an external pilot (EP), who is located at an airport and is responsible for takeoff and landing of the aircraft via hand-held controller. On takeoff, once the aircraft is airborne, the EP transfers control of the aircraft to the pilot-in-command and before the aircraft reaches the runway on arrival, the pilot-in-command transfers control of the aircraft to the EP to land the aircraft. The payload operator is a crewmember that operates the payload on the UAS (e.g., a camera for target search or sensors for chemical monitoring). Visual observers are personnel who remain in visual contact with the UAS and communicate with the pilot-in-command instructions to avoid obstacles. The mission commander is defined as any crewmember that manages and coordinates the crew without operating the vehicle or payload him/herself.

3.2.3.5 Control Station

The control station portion of the taxonomy addresses the information about the control station used to operate the UAS. The three main subcategories defining a control station are the hardware, control device(s), and information display(s). Regarding hardware, a setup was considered a "desktop" if it contained one or two monitors arranged side-by-side, whereas a "suite" was considered to have three or more monitors which may have been on a desk or arranged horizontally and/or vertically. The details of this portion of the taxonomy include the following:

1. Hardware
    a. Suite (multiple workstations with multiple control devices and monitors which may arranged in horizontal or vertical configurations)
    b. Desktop (with one or two monitors)
    c. Laptop/mobile device
2. Control Device
    a. Stick-and-throttle
    b. Joystick
    c. Point-and-click
    d. Knobs
    e. Touch Screen
    f. Keyboard
3. Information Display
    a. Out-window
    b. Moving Map
    c. System Status
    d. Traffic Information
    e. Weather Information
    f. Payload Status
    g. Communication Client
    h. Vertical Situation Display
    i. Navigation Display
    j. Electronic Checklist
    k. Horizontal Situation Indicator

3.2.3.6 Ownship

Ownship refers to the type of UAS operated (RTCA Inc., 2010; Scheff, 2014; Williams, 2007). The types considered include:

1. A160 Hummingbird
2. AAI Aerosonde Mark 4.7
3. ACR Manta
4. ACR Silver Fox
5. ADCOM YABHON
6. Aero Design and Development Hornet
7. Aeronautics Defense Systems Aerolight
8. Aeronautics Defense Systems Aerosky

9. Aeronautics Defense Systems Aerostar
10. Aeroscout B1-100
11. Aeroscout Scout B1-100
12. Aerosonde Mk47
13. Aerosystems ZALA 421
14. AeroVironment Helios
15. AeroVironment Pathfinder
16. AeroVironment Puma
17. AeroVironment Raven B
18. Arcturus T-20
19. ATE Vulture
20. Aurora Flight Sciences Centaur
21. Aurora Flight Sciences Excalibur
22. Aurora Flight Sciences Goldeneye-80
23. Aurora Flight Sciences Orion
24. Aurora Flight Sciences Perseus
25. BAE Systems Kingfisher
26. BAE Systems Phoenix
27. BAE Systems Silverfox
28. BAE Systems Skylynx
29. Baykar Makina
30. Bell 206
31. Bell Helicopter Textron Eagle
32. Boeing Insight
33. Boeing Integrator
34. Cessna 172
35. Cessna 182
36. Cessna Caravan
37. Cyber Tech CyberEye
38. Cyber Tech CyberQuad
39. Cyber Tech CyberWraith
40. Cyber Tech CyBird
41. Dara Aviation D-1
42. DarkStar
43. Denel Dynamics Bateleur
44. Denel Dynamics Seeker
45. DRS Neptune RQ-15
46. EADS Dornier
47. Elbit Systems Hermes
48. EMIT Sparrow
49. EMT LUNA X-2000
50. ENICS BERTA
51. ENICS E08 Aerial Decoy
52. Explorer Tandem Wing
53. Fuji RPH-2A
54. General Atomics Altair

55. Generic Helicopter
56. Generic MALE
57. Generic Multirotor
58. Global Observer HALE
59. GNAT 750
60. Gulfstream 550
61. Heron
62. Honeywell RQ-16A T-Hawk
63. Hummingbird A-160
64. Husky Autonomous Helicopter
65. IAI NRUAV
66. Innocon MicroFalcon
67. Innocon minFalcon
68. Integrated Dynamics Border Eagle
69. Integrated Dynamics Explorer
70. Integrated Dynamics Hawk
71. Integrated Dynamics Vector
72. Integrated Dynamics Vision MK
73. International Aviation Supply Raffaello
74. King Air 200
75. L-3 TigerShark
76. L-3 Viking
77. MBDA Fire Shadow
78. Meggitt Barracuda
79. Meggitt Hammerhead
80. Meggitt Vindicator
81. MLB Super Bat
82. MQ-1 Predator A
83. MQ-1C ER/MP Sky Warrior/Gray Eagle
84. MQ-9 Predator B/Reaper
85. MSI BQM
86. MSI Chukar
87. MSI Falconet
88. MSI Firejet
89. MSI High Speed Maneuvarable Surface Target
90. MSI MQM
91. MSI QST-35
92. MSI QUH-1 Rotary Wing
93. Northrup Grumman BAT-12
94. Northrup Grumman LEMV Airship
95. Ranger
96. Raven
97. Raytheon Cobra
98. Raytheon KillerBee
99. Rheinmetall Fledermaus
100. Rheinmetall KZO

101. Rheinmetall Mucked
102. Rheinmetall OPALE
103. Rheinmetall Tares/Taifun
104. RMAX TYPE II
105. Rodian/Automasjonsutvikling AS Xr-T8
106. Rodian/Automasjonsutvikling AS Xr-T9
107. RQ-2 Pioneer
108. RQ-4 Global Hawk
109. RQ-5 Hunter
110. RQ-6 Outrider
111. RQ-7 Shadow
112. RQ-8A FireScout
113. SA 60 LAA
114. SA-200 Weasel
115. Sagum Crecerelle
116. Sagum Patroller
117. Sagum Sperwer
118. SAIC Vigilante
119. Satuma Flamingo
120. Satuma Jasoos
121. Satuma Mukhbar
122. ScanEagle
123. Schiebel Camcopter
124. Selex Galileo Falco
125. Selex Galileo Mirach
126. Skycam Hawk
127. Snap Defense Systems Aggressor
128. Snap Defense Systems Bandit
129. Snap Defense Systems Blacklash
130. Snap Defense Systems Centurion
131. Snap Defense Systems Scout
132. Snap Defense Systems Sea Vixen
133. Snap Defense Systems Stingray
134. TAI ANKA
135. Thales Watchkeeper WK450
136. Ucon System RemoEye
137. Unmanned Systems Group ATRO-X
138. Unmanned Systems Group CT-450 Discover 1
139. Unspecified
140. Uvision Blade Arrow
141. Uvision Blue Horizon
142. Uvision MALE UAS
143. Uvision Sparrow
144. Warrior Gull
145. WLD 1B
146. X-47B N-UCAS

147. Xian ASN

3.2.4 Type of Study

The type of study identifies the experiment methodology used by the researchers. Some documents may include more than one type. The types of study considered in this review include:

1. Human-in-the-loop Simulation
2. Field Test
3. Accident Data Analysis
4. Literature Review/Meta Analysis
    a. General Human-Automation Interaction
    b. UAS-Specific
5. Products of the Systems Engineering Lifecycle
    a. Operational Concept/Integration Plan
    b. Requirements/Design Recommendations
    c. Design
    d. Prototype
6. Human Factors Design and Evaluation of an Existing System
    a. Task Analysis
    b. Observation
    c. Participant Questionnaire
    d. Heuristic Evaluation
    e. Think-Aloud Verbal Protocol
    f. Subject Matter Expert Interview
    g. Focus Group
7. Computational Modeling
    a. Agent Based Simulation
    b. Discrete Event Simulation
    c. Markov Decision Process

3.3 CATEGORIZATION SUMMARY

This section reports the number of categorizations for each part of the taxonomy reported in Section 3.2.

3.3.1 Function Allocation Strategy

Reported in Table 7, a majority of the studies focused on automation at the information processing stages of information analysis, decision and action selection, and/or action implementation. Within the information acquisition stage of processing, a majority of the studies used a processed data presentation LOA. In the information analysis stage, there was little use of LOAs with mixed initiative constraints; most of the studies did not permit the human operator to set thresholds or constraints on the automation. For the decision and action selection stage of processing, a majority of the studies used either no decision and action selection automation (24 documents) or a high level of decision and action selection automation (i.e., management by consent, management by exception, and fully automated decision selection; 35 documents). Finally, in the action implementation stage of processing, a substantial majority of the documents reviewed either allocated implementation to the human operator or, when implementation was automated, the human operator was necessarily informed.

Table 7. Document categorizations for function allocation strategy.

Category	**Total**
Information Acquisition	21
Single Information Source	5
None	2
Assisted	0
Processed Data Presentation	3
Mixed Initiative Data Presentation	0
Multiple Information Sources	18
None	2
Assisted	0
Processed Data Presentation	16
Mixed Initiative Data Presentation	0
Information Analysis	65
None	4
Mixed Initiative Reference Generation	0
Automated Reference Generation	1
Automated Situation Assessment	18
Automated Situation Assessment and Reference Generation	12
Automated Situation Assessment and Reference Generation with Alerting	26
Automated Situation Assessment and Mixed Initiative Reference Generation	0
Automated Situation Assessment and Mixed Initiative Reference Generation with Alerting	0
Mixed Initiative Situation Assessment	1
Mixed Initiative Situation Assessment and Automated Reference Generation	1
Mixed Initiative Situation Assessment and Automated Reference Generation with Alerting	0
Mixed Initiative Situation Assessment and Reference Generation	1
Mixed Initiative Situation Assessment and Reference Generation with Alerting	1
Decision and Action Selection	78
None	24
Assisted Option Generation	8
Automated Option Generation	4
Filtered Option Generation	3
Automated Option Ordering	0
Mixed Initiative Option Generation	2
Management by Consent	12
Management by Exception	12
Mixed Initiative Decision Selection	2
Fully Automated Decision Selection	11

Action Implementation	55
None	28
Compulsory Feedback	23
Feedback by Request	0
Feedback by Design	0
No Feedback	4
Automation Reliability	3
>90%	1
80%-90%	1
70%-80%	0
60%-70%	1
50%-60%	0
40%-50%	0
30%-40%	0
20%-30%	0
10%-20%	0
<10%	0

3.3.2 Measures

Operator cognitive workload and SA, both falling under the categorization of human-automation interaction measures, were the most-used measures across the documents reviewed (see Table 8). Regarding more objective measures, hit rate and miss rate were used frequently in the literature, typically to measure operator ability to either notice an abnormal system state, such as navigation automation failure or low fuel. Another widely-used objective measure was RT, which typically measured the time elapsed between the onset of an alert and the time for the operator to take action to correct the system.

Table 8. Document categorizations for measures.

Category	**Total**
Function Allocation	2
System Workload/Taskload	2
Mismatches Between Responsibility and Authority	0
Work Environment Stability	0
Function Allocation Coherence	0
Interruptions	0
Automation Boundary Conditions	0
Adaptation to Context	0
Human-Automation Interaction	34
Mental Workload	19
Situation Awareness	11
Complacency	0
Skill Degradation	0

Trust	2
Reliance	1
Utilization	1
Mission Performance	21
Fuel Consumption	0
Conflict Resolution Maneuver Quality	13
Delay	0
Compliance	0
Flight Path Error	5
Lateral	5
Vertical	0
Speed Error	1
Training Required to Meet Performance Criterion	0
Landing Performance	0
Nose Position	0
Lateral Velocity	0
Vertical Velocity	0
Distance Off Centerline	0
Glideslope Error	0
Attention Allocation	1
Fixation Frequency	0
Glance Duration	0
Fixation Duration	0
Total Viewing Time	1
Subjective Usability	4
Detection and Assessment	12
Signal Detection	12
Sensitivity	12
Hit Rate	9
Miss Rate	2
Correct Rejection Rate	1
False Alarm Rate	0
Response Bias	0
Lens Model	0
Accuracy	0
Consistency	0
Judgment Strategy	0
Skill Score	0
Skill Score	0
Conditional Bias	0
Unconditional Bias	0
Category	**Total**
Control	18
Response Time	18
Alert	10

Air Traffic Control	1
Target	5
Airspace Configuration	1
Abnormal System Status	1
Target Tracking Performance	0
Fitts' Law	0

3.3.3 Task

The task(s) in which the UAS operator was engaged is presented in Table 9. A majority of the documents reviewed reported UAS operations in the aerial work/mission phase of flight, and most of the missions were in a military context. Regarding generic functions associated with UAS operation, a relatively low proportion of documents required communication tasks, as most were focused on *manage*, *aviate*, and *navigate* tasks.

Table 9. Document categorizations for task.

Category	**Total**
Phase of Flight	43
Flight Planning	1
Engine Start	0
Taxi	0
Takeoff	2
Departure	3
En Route	7
Aerial Work/Mission	23
Descent	1
Approach	4
Landing	2
Generic Functions	223
Manage	62
Plan for Normal Conditions	6
Plan for Non-normal Conditions	1
Make Decisions in Normal Conditions	26
Recognize and Respond to Non-normal Conditions	24
Transfer Control	5
Aviate	72
Monitor and Control Aircraft Systems (Including Automation)	32
Monitor Consumable Resources	13
Monitor and Configure Control Station	3
Maneuver Aircraft to Avoid Collision	20
Monitor and Control Status of Control Links	4
Navigate	59
Control and Monitor Aircraft Location and Flight Path	30

Remain Clear of Terrain, Airspace Boundaries, and Weather	11
Self-separate from other Aircraft	16
Ensure Lost Link Procedure Remains Appropriate	1
Terminate Flight	1
Communicate	30
Air Traffic Control	16
Ground Control	0
Local Control	0
Terminal Radar Approach Control	6
Air Route Traffic Control Center	10
Pilots of other Aircraft	0
Crew Members	12
Ancillary Services (e.g., Weather)	1
Mission	29
Military	21
Reconnaissance/Surveillance	6
Tactical Strike	0
Communication Relay	0
Signal Intelligence	1
Maritime Patrol	0
Penetrating Strike	1
Suppression of Enemy Air Defenses (SEAD)	0
Aerial Refueling	0
Counter Air	0
Airlift	0
Target Search	6
Target Identification	7
Civil	8
Atmospheric Research	0
Border Patrol	0
Disaster Response	0
Hurricane Measurement and Tracking	0
Forest Fire Monitoring and Support	3
Search and Rescue	0
Maritime Surveillance	3
Law Enforcement	0
Humanitarian Aid	0
Aerial Imaging and Mapping	0
Drug Surveillance and Interdiction	0
Monitor and Inspect Critical Infrastructure	0
Natural Hazard Monitoring	0
Airborne Pollution Observation and Tracking	1
Chemicals and Petroleum Spill Monitoring	0
Communications Relay	0
Traffic Monitoring	1

Port Security	0
Commercial	0
Crop Monitoring	0
Fish Spotting	0
Remote Imaging and Mapping	0
Utility Inspections	0
Mining Exploration	0
Agricultural Applications	0
Communication Relay	0
Petroleum Spill Monitoring	0
Site Security	0
Broadcast Services	0
News Media Support	0
Filming	0
Real Estate Photos	0
Aerial Advertising	0
Cargo	0
Flight Event	15
Nominal	6
Failure	9
Vehicle Equipment	8
Control Station Equipment	0
Control Link	1
ATC Communication	0

3.3.4 Environment

The environment categorizations, shown in Table 10, reveal little manipulation of atmospheric conditions or geography for RPICs to fly through. However, many documents required RPICs to deal with intruder traffic, either by self-separation or in coordination with ATC.

Table 10. Document categorizations for environment.

Category	**Total**
Atmospheric	3
Wind	0
Visibility	0
Weather	2
Sky Conditions	0
Air Temperature	0
Pressure	0
Precipitation	0
Turbulence	1
Ice	0

Lighting	0
Day	0
Night	0
Intruder Traffic	32
Vehicle Type	8
Airship	0
Glider	0
Helicopter	0
Manned Powered Aircraft	8
Unmanned Powered Aircraft	0
Position Broadcast Equipment	3
Radar-Based	0
Satellite-Based	0
ADS-B	1
Mixed	2
None	8
Density	21
None	8
Unspecified	4
<5 Intruder Encounters	4
5-10 Intruder Encounters	5
>10 Intruder Encounters	0
Geography	10
Restricted Airspace	3
Buildings	1
Natural Obstacle	4
No Obstacles	1
Other Obstacle	1

3.3.5 National Airspace Context

Many of the documents reviewed did not provide any explicit indication of the airspace through which the UAS was operated, reflected by the relatively small numbers of categorizations in Table 11. Of those documents that did report airspace context, a majority utilized instrument flight rule (IFR) airspace.

Table 11. Document categorizations for national airspace context.

Category	**Total**
Airspace	11
Class A	2
Class B	2
Class C	2
Class D	1

Class E Below A	1
Class E Above A	0
Class G	0
Oceanic	1
Surface	0
Airport (Ramp, Taxiway, Runway)	0
Non-airport Ground	0
Watercraft	0
Flight Rules	10
Visual Flight Rules	1
Instrument Flight Rules	9

3.3.6 Participants/Crew

Shown in Table 12, a majority of the documents reviewed required participants to either be a certified pilot or to have experience operating UASs. Additionally, some documents included other crewmembers, such as EPs, payload operators, visual observers, or mission commanders.

Table 12. Document categorizations for participants/crew.

Category	**Total**
Pilot-in-command	37
Manned Aircraft Experience	14
Unmanned Aircraft Experience	9
Mixed Experience	2
No Prior Flying Experience	8
Unspecified	2
External Pilot	2
Payload Operator	2
Visual Observer	2
Ground	1
Airborne	1
Mission Commander	3

3.3.7 Control Station

Generally, control station setups in the documents reviewed either featured a desktop computer running a UAS simulation, or a suite modeled after an operational control station (reported in Table 13). Regarding control devices, a majority of the control stations featured a mouse and keyboard setup, for which RPICs were required to control the UAS by delivering mouse-click and/or keyboard commands to the interface. Finally, navigation displays and moving map displays were most prominent in the control stations, with electronic checklist displays and horizontal situation indicators used very infrequently.

Table 13. Document categorizations for control station.

Category	Total
Hardware	26
Suite	12
Desktop	13
Laptop	1
Control Device	0
Stick-and-throttle	3
Joystick	9
Point-and-click	21
Knobs	0
Touch Screen	1
Keyboard	15
Information Display	128
Out-window	16
Moving Map	25
System Status	17
Traffic Information	15
Weather Information	3
Payload Status	6
Communication Client	14
Vertical Situation Display	5
Navigation Display	25
Electronic Checklist	2
Horizontal Situation Indicator	0

3.3.8 Ownship

The vehicles used across the documents reviewed are reported in Table 14. Many human-in-the-loop studies did not specify the aircraft that the simulation modeled (evidenced by the 11 categorizations of *unspecified* aircraft). Of those that specified which aircraft was modeled, the Predator B/ Reaper was the most used.

Table 14. Document categorizations for ownship.

Category	Total
A160 Hummingbird	0
AAI Aerosonde Mark 4.7	0
ACR Manta	0
ACR Silver Fox	0
ADCOM YABHON	0
Aero Design and Development Hornet	0
Aeronautics Defense Systems Aerolight	0
Aeronautics Defense Systems Aerosky	0

Aeronautics Defense Systems Aerostar	0
Aeroscout B1-100	0
Aeroscout Scout B1-100	0
Aerosonde Mk47	0
Aerosystems ZALA 421	0
AeroVironment Helios	1
AeroVironment Pathfinder	1
AeroVironment Puma	1
AeroVironment Raven B	1
Arcturus T-20	0
ATE Vulture	0
Aurora Flight Sciences Centaur	0
Aurora Flight Sciences Excalibur	0
Aurora Flight Sciences Goldeneye-80	1
Aurora Flight Sciences Orion	0
Aurora Flight Sciences Perseus	1
BAE Systems Kingfisher	0
BAE Systems Phoenix	0
BAE Systems Silverfox	0
BAE Systems Skylynx	0
Baykar Makina	0
Bell 206	0
Bell Helicopter Textron Eagle	1
Boeing Insight	0
Boeing Integrator	0
Cessna 172	1
Cessna 182	0
Cessna Caravan	0
Cyber Tech CyberEye	0
Cyber Tech CyberQuad	0
Cyber Tech CyberWraith	0
Cyber Tech CyBird	0
Dara Aviation D-1	0
DarkStar	0
Denel Dynamics Bateleur	0
Denel Dynamics Seeker	0
DRS Neptune RQ-15	0
EADS Dornier	0
Elbit Systems Hermes	0
EMIT Sparrow	0
EMT LUNA X-2000	0
ENICS BERTA	0
ENICS E08 Aerial Decoy	0
Explorer Tandem Wing	0
Fuji RPH-2A	0

General Atomics Altair	1
Generic Helicopter	1
Generic MALE	4
Generic Multirotor	1
Global Observer HALE	0
GNAT 750	0
Gulfstream 550	0
Heron	0
Honeywell RQ-16A T-Hawk	0
Hummingbird A-160	0
Husky Autonomous Helicopter	0
IAI NRUAV	0
Innocon MicroFalcon	0
Innocon minFalcon	0
Integrated Dynamics Border Eagle	0
Integrated Dynamics Explorer	0
Integrated Dynamics Hawk	0
Integrated Dynamics Vector	0
Integrated Dynamics Vision MK	0
International Aviation Supply Raffaello	0
King Air 200	0
L-3 TigerShark	0
L-3 Viking	0
MBDA Fire Shadow	0
Meggitt Barracuda	0
Meggitt Hammerhead	0
Meggitt Vindicator	0
MLB Super Bat	0
MQ-1 Predator A	3
MQ-1C ER/MP Sky Warrior/Gray Eagle	0
MQ-9 Predator B/Reaper	7
MSI BQM	0
MSI Chukar	0
MSI Falconet	0
MSI Firejet	0
MSI High Speed Maneuvarable Surface Target	0
MSI MQM	0
MSI QST-35	0
MSI QUH-1 Rotary Wing	0
Northrup Grumman BAT-12	0
Northrup Grumman LEMV Airship	0
Ranger	0
Raven	0
Raytheon Cobra	0
Raytheon KillerBee	0

Rheinmetall Fledermaus	0
Rheinmetall KZO	0
Rheinmetall Mucked	0
Rheinmetall OPALE	0
Rheinmetall Tares/Taifun	0
RMAX TYPE II	0
Rodian/Automasjonsutvikling AS Xr-T8	0
Rodian/Automasjonsutvikling AS Xr-T9	0
RQ-2 Pioneer	2
RQ-4 Global Hawk	1
RQ-5 Hunter	2
RQ-6 Outrider	1
RQ-7 Shadow	4
RQ-8A FireScout	1
SA 60 LAA	0
SA-200 Weasel	0
Sagum Crecerelle	0
Sagum Patroller	0
Sagum Sperwer	0
SAIC Vigilante	0
Satuma Flamingo	0
Satuma Jasoos	0
Satuma Mukhbar	0
ScanEagle	0
Schiebel Camcopter	0
Selex Galileo Falco	0
Selex Galileo Mirach	0
Skycam Hawk	0
Snap Defense Systems Aggressor	0
Snap Defense Systems Bandit	0
Snap Defense Systems Blacklash	0
Snap Defense Systems Centurion	0
Snap Defense Systems Scout	0
Snap Defense Systems Sea Vixen	0
Snap Defense Systems Stingray	0
TAI ANKA	0
Thales Watchkeeper WK450	0
UCon System RemoEye	0
Unmanned Systems Group ATRO-X	0
Unmanned Systems Group CT-450 Discover 1	0
Unspecified	11
UVision Blade Arrow	0
UVision Blue Horizon	0
UVision MALE UAS	0
UVision Sparrow	0

Warrior Gull	0
WLD 1B	0
X-47B N-UCAS	0
Xian ASN	0

3.3.9 Type of Study

The number of each type of study approach used across the documents is reported in Table 15. A majority of the studies used either a human-in-the-loop simulation, or presented the results of a literature review/meta-analysis. Various human factors design and evaluation techniques were also used, with a majority within that category being task analyses or SME interviews.

Table 15. Document categorizations for type of study.

Category	**Total**
Accident Data Analysis	6
Computational Modeling	4
Agent Based Simulation	0
Discrete Event Simulation	2
Markov Decision Process	2
Field Test	1
Human Factors Design and Evaluation of an Existing System	19
Task Analysis	9
Observation	1
Participant Questionnaire	1
Heuristic Evaluation	0
Think-Aloud Verbal Protocol	2
Subject Matter Expert Interview	6
Focus Group	0
Human-in-the-loop Simulation	27
Literature Review/Meta Analysis	25
General HAI	15
UAS-Specific	10
Products of the Systems Engineering Lifecycle	15
Operational Concept/Integration Plan	4
Requirements/Design Recommendations	8
Design	2
Prototype	1

3.4 LITERATURE REVIEW

The literature review is organized by phase of flight reported by Hobbs and Lyall (2015), shown in Figure 2. Where applicable, subsections within the phases of flight represent generic tasks that are required within that phase of flight (e.g., the en route phase of flight is subdivided by vehicle control and detect-and-avoid tasks). When a document contained multiple tasks, it was included in the task subsection for which the automation was applied. The *detect and avoid* (DAA) task represented the procedures in detecting a conflict (such as with an intruder aircraft and terrain) while the path *re-planning* task represented longer-term navigation changes to the aircraft's cleared route of travel. Finally, the review is presented paper-by-paper, with an emphasis on the task conducted and the LOA used to assist the RPIC. Summaries of all papers included in the literature review are presented in the annotated bibliography in Appendix A3.

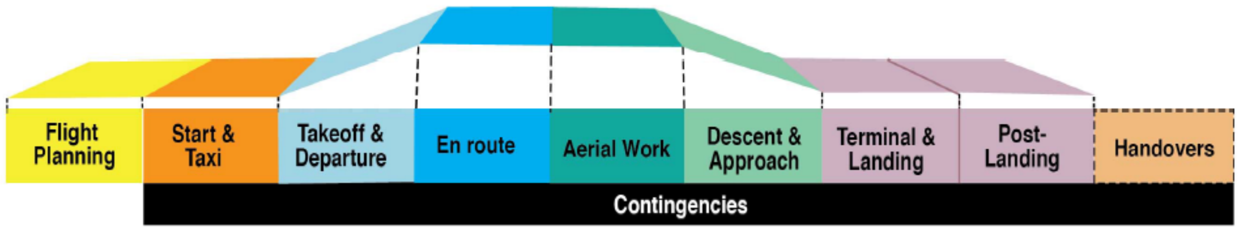

Figure 2: UAS phases of flight, as reported by Hobbs and Lyall (2015).

Please note that in this review, the term unmanned aerial vehicle (UAV) is used when the aircraft itself is considered and UAS for the system.

3.4.1 Flight Planning

In their taxonomy of current and potential future UAS missions, Nehme et al. (2007) identified path planning (and re-planning) supervision as one of the basic tasks to occur most frequently across UAS mission types. Path planning is a complex, multivariate optimization problem that requires high-level cognition, making it a good candidate for automation. Similarly, Barnes, Knapp, Tillman, Walters, and Velicki (2000), via the results of their discrete event simulation of the Outrider UAS platform, identified *analysis and modification of the mission plan* as a critical procedure requiring three or more steps, making it a good candidate for automation. Furthermore, the task *enter way points and prepare flight plan* scored highly in the visual, auditory, cognitive, and psychomotor (VACP) workload scale, indicating that the task imposes a high level of workload on the UAS crew.

In an attempt to mitigate the cognitive loading associated with the planning task, Rudnick, Clauß, and Schulte (2014) conducted a field test of a supervisory control architecture using fixed-wing and rotorcraft UASs. Their field test showed that it is possible to automate planning and re-planning in a real-world UAS. Participants monitored the supervisory control system during target search and reconnaissance missions, while an experimenter triggered events (e.g., blocking a corridor of airspace) to assess the automated planning and re-planning functionalities of the UAS. While the automation was successful in performing the mission, there was no human factors assessment of the effects on the human operator.

To assess the human factors implications of automated planning, Shively, Neiswander, and Fern (2011) compared manual control of a UAS versus supervisory control via a *Playbook* interface. Results revealed that the manual control condition, which required mission planning at the start of the scenario via a waypoint-editing interface, yielded longer average planning time and higher NASA Task Load Index (NASA-TLX) workload than the supervisory control condition, in which the route plan was generated at a fully automated level of decision and action selection automation. However, in their experiment, participants were expected to plan a short route while under pressure to plan the route as quickly as possible. This context likely does not match the planning context of current and future UAS operations in the NAS.

3.4.1.1 Summary of Literature in the Flight Planning Phase of Flight

The results across the studies suggest that route planning is a highly demanding task, and automating the task is not only feasible in a real-world UAS, but also may reduce RPIC workload and the time necessary for mission planning. However, there is a paucity of studies assessing the effect of automated flight planning on SA or the ability to re-plan upon system failure, which should be taken into consideration when using automating to assist the crew during the flight planning process. Furthermore, there is little work investigating the effects of automation on planning in a context similar to expected future UAS operation in the NAS, making it an area requiring more research.

3.4.2 Takeoff and Departure

Barnes et al. (2000) identified *perform takeoff procedures* as a critical function, making it a good candidate for automation. However, the results of their discrete event simulation suggest that the takeoff phase did not impose high VACP workload on the Outrider crew. Related to this, a review of military UAS accidents and incidents revealed the difficulty RPICs have in the takeoff and landing portions of flight, particularly when an EP is used (Williams, 2004). In some military UASs (e.g., Pioneer and Hunter), the EP, who is within visual-line-of-sight of the aircraft, performs takeoff procedures via a hand-held controller. Once the vehicle is in the air, the EP transfers control to the pilot-in-command, who is located in a GCS. Opposite to these aircraft, the pilot-in-command performs takeoffs for the Predator UAS, and the takeoff procedures for the Global Hawk and Shadow are fully automated. The takeoff accident rates for these systems are substantially lower than for those that use an EP, suggesting that UASs used in civil and commercial operations should not use an EP to perform takeoff procedures.

De Vries, Koeners, Roefs, Van Ginkel, and Theunissen (2006) conducted two human-in-the-loop simulations of departures and approaches to assess the effects of three LOAs (three for terrain avoidance and three for intruder avoidance) on RPIC ability to avoid conflicts with terrain and intruders. With the exception of the lowest LOA for intruder and terrain avoidance automation (which were at an information analysis level of automated situation assessment; the remaining were at a level of automated situation assessment and reference generation with alerting), the experiments manipulated the level of action implementation automation, providing the RPIC with levels of no automation (i.e., manual implementation), compulsory feedback, and no feedback. The lowest intruder and terrain detection LOAs included alerting the RPIC of a potential conflict with terrain, and providing a resolution for the RPIC to use to avoid conflict with an intruder (the RPIC had no override authority; (s)he was required to perform the maneuver given by the automation). In the medium LOA, the terrain and intruder avoidance maneuvers were automatically implemented and the RPIC was necessarily informed. In the highest LOA, the automation implemented a resolution maneuver to avoid terrain and intruders without informing the RPIC of the maneuver. Experiment 1 results revealed no statistical difference among the LOAs in terms of the number of user interventions (i.e., maneuvering for a conflict before it was detected by the automation), the number of conflicts, or SA. For the second experiment, a series of display changes were made, and only the low and medium LOAs were tested, but there was a continued lack of significant differences among the LOAs. In the experiments, the simulation was paused and screens were blacked out upon detecting a conflict, which may have decreased the realism of the experiment, leading to the lack of statistical significance. Furthermore, although participants were good at detecting conflicts before the automation, they struggled constructing effective and efficient maneuvers for avoiding collisions. The results suggest that maneuver options should be provided to the RPIC, particularly during high-workload phases of flight such as departure. However, more work needs to be done in the takeoff phase of flight to assess the effects of different function allocation strategies.

3.4.2.1 Summary of Literature in the Takeoff and Departure Phases of Flight

Takeoff and departure procedures have high workload demands, which may contribute to the findings of Williams (2004) that this phase of flight yields high accident rates. Despite this finding, little work has been done assessing automation strategies to mitigate the difficulty associated with takeoff and departure procedures. The two human-in-the-loop experiments conducted by De Vries et al. (2006) revealed a lack of significant differences among the automation levels, but the automation was focused on the task of detecting and avoiding terrain and intruders, rather than automating control of the UAV during takeoff and departure. The results of the accident analysis reported by Williams (2004) suggests that takeoff procedures should be fully automated, placing the RPIC in a supervisory control role during the phase of flight. However, more work needs to be done on the potential negative consequences of this automation strategy.

3.4.3 En Route

The en route phase of flight describes the flight path between the top-of-climb and the area where the aerial work is performed. UAS functions typically automated during the en route phase of flight include vehicle control and detect-and-avoid automation.

3.4.3.1 Vehicle Control

Regarding automation of UAS functions in the en route phase of flight, Williams (2012) conducted a human-in-the-loop simulation experiment assessing two flight control LOAs on flight technical error, response rate to heading control and engine failures, traffic monitoring, awareness of relative position, and workload measured by NASA-TLX. In the *vector control* condition, participants controlled heading and altitude by using the mouse to specify heading and altitude values; in the *waypoint control* condition, RPICs controlled vehicle heading by adding or moving waypoints on a navigation display, and specifying the altitude at each waypoint. The *vector control* condition represents a decision and action selection LOA of none (i.e., manual heading and altitude selection), while the *waypoint control* condition represents a decision and action selection level of mixed initiative decision selection. The level of control automation had no statistically significant effect on responses to system failures, number of responses to intruder traffic (participants were required to verbally indicate nearby traffic), awareness of relative position, or NASA-TLX scores. However, the *waypoint control* automation led to lower flight technical error than the vector control automation, particularly for inexperienced pilots. The results suggest that waypoint-editing may yield lower flight technical error than a vector control interface, but there was largely no difference between the two. Interestingly, the higher automation level did not free enough RPIC resources to significantly affect system failure responses, suggesting that RPIC workload generally was low throughout the task. The general lack of difference may be due to the fact that both control levels represent relatively high levels of control automation.

Calhoun et al. (2013) conducted a usability test on an adaptable interface in which participants controlled three UAVs while "thinking aloud" about the interface. Four control modes were available to the participants, and they were free to switch between control modes at will (reflecting an adaptable automation paradigm in which participants could freely switch among differing levels of decision and action selection and action implementation automation (Miller & Parasuraman, 2007)). The *manual* mode consisted of stick-and-throttle control (a control automation decision and action selection LOA of none and an action implementation LOA of none). In the *noodle control* mode, participants used the stick and throttle controls to establish precise near-future trajectories with specific heading and altitude changes, reflecting a decision and action selection LOA of none and action implementation LOA of compulsory feedback. In the *maneuver control* mode, a UAS was instructed to perform a short, well-defined change in flight path (e.g., if the participant gave the command "hook left," the UAV automatically performed the pre-defined maneuver). This level of control represents a decision and action selection LOA of mixed initiative option generation, and an action implementation LOA of compulsory feedback. Finally, in the *play control* mode, participants specified a task, and the automation controlled and coordinated the UAVs to complete the task. This control represented decision and action selection and action implementation LOAs of mixed initiative decision selection and compulsory feedback, respectively. Participant comments revealed favorable attitudes toward the adaptable nature of the setup (i.e., the ability to freely switch between control modes), and stressed the importance of being able to switch between control modes easily. This corroborates the conclusions by Jenkins (2012) and Miller and Parasuraman (2007), who both stressed the importance of flexibility in automation and ensuring the RPIC has the ability to allocate tasks to automated agents. Although the experiment was performed using a three-vehicle scenario, the findings are likely relevant to single-UAV operation required for the NAS.

3.4.3.2 Detect and Avoid

A majority of the literature in the en route domain has assessed LOAs for UAS DAA tasks. Related to this, a human-in-the-loop experiment was conducted to determine the minimum information requirements for the DAA task (Friedman-Berg, Rein, & Racine, 2014). Four levels of information were presented to RPICs, including *position* (which displayed only the current position of intruders), *direction* (which displayed *position* information as well as horizontal and vertical directionality), *prediction* (which displayed *position* and *direction* information as well as color-coded collision alerts and future-position vector line projections), and *rate* (which displayed *position*, *direction*, and *prediction* information as well as ground speed, climb/descent rate, and turn rate). These four information levels reflected two levels of information analysis automation: the *position* and *direction* displays reflected a LOA of automated situation assessment, while the *prediction* and *rate* displays reflected automated situation assessment and reference generation with alerting. Dependent variables included subjective questionnaire responses, number of near mid-air collisions, minimum separation from an intruder, intruder tau values, and the visual attention distribution across the displays. Objective responses tended to plateau at the *prediction* level of information while not imposing significantly higher workload or requiring more attention than the lower levels of information. Interestingly, the plateau occurred at the crossover between the LOA of automated situation assessment and the LOA of automated situation assessment and reference generation with alerting, suggesting that RPICs require a level of at least alerting successfully perform the DAA task.

In a human-in-the-loop experiment assessing the effects of maneuver selection and implementation automation, Kenny and Fern (2012) asked participants to fly a pre-planned flight plan while responding to TCAS alerts and communicating with ATC (note: pilots flew a "signal intelligence" mission, but there were no details suggesting that the mission required attentional and/or cognitive resources beyond those required with regular en route fight; thus, the findings are most relevant to the en route phase of flight). Four levels of vertical control automation, for responding to TCAS resolution advisories (RAs), were assessed: (1) waypoint control, (2) altitude hold control, (3) management by exception, and (4) fully automated. Under waypoint control, participants were required to click on waypoints to drag them (horizontal control) and enter altitudes via keyboard input, reflecting a decision and action selection LOA of management by consent (participant could accept or reject RA) and action implementation LOA of no automation (i.e., manual altitude selection). In the altitude hold control condition, participants manually entered the new altitude, which was automatically assigned to the next waypoint on the route (TCAS gives only vertical RAs, reflecting a decision and action selection LOA of management by consent and no action implementation LOA). In the management by exception condition, the automation selected the TCAS RA if the RPIC did not override it (a decision and action selection LOA of management by exception, with action implementation LOA of no automation). Finally in the full automation condition, TCAS RAs were applied automatically and the RPIC was necessarily notified (decision and action selection: full automation; action implementation: compulsory feedback). RT to RAs was significantly faster in the management by exception condition than in the manual and knobs conditions. There was no significant difference in RPIC response rate across conditions, but there was a significant difference in compliance rates (responding correctly to a RA) such that management by exception yielded a significantly higher compliance rate than the waypoint and altitude hold conditions. Significant NASA-TLX differences were revealed in the physical and temporal dimensions; the waypoint condition generally yielded higher ratings than the remaining three LOAs. In general, the results reveal the potential benefits of the management by exception approach to responses to TCAS RAs; this approach yielded the fastest RT and highest compliance rate while not significantly increasing workload ratings. Furthermore, the results reveal that the waypoint editing and altitude hold conditions (both at decision and action selection LOA of management by consent) are unacceptable for timely response to TCAS RAs.

Another human-in-the-loop experiment assessed the effect of including a traffic display in the GCS as well as two levels of traffic density when separation responsibility was allocated to ATC (Fern, Kenny, Shively, & Johnson, 2012). The traffic display presented intruder positions, color-coded relative altitude, and intruder trajectories. The display-absent condition was at information acquisition and information analysis levels of no automation, while the display-present condition featured information acquisition automation at a level of processed data presentation from multiple sources and information analysis LOA of automated situation assessment and reference generation. RPICs were required to reroute the UAS when issued instructions from a mission commander, communicate any changes with ATC, and respond to ATC maneuvering instructions. Participants flew a pre-filed flight plan to conduct a highway patrol mission, but the mission did not impose any tasks that differed from normal en route flight. Objective responses included minimum horizontal and vertical distance from conflicting intruders and the number of losses of separation; NASA-TLX ratings and Likert scale ratings were collected to measure subjective perceptions of workload, and SA was measured by asking pilots six questions and asking for their responses on a Likert scale. The inclusion of the traffic display had no statistically significant effects on any of the objective measures nor any NASA-TLX effects. However, participants rated their workload in communicating with ATC (via Likert scale responses) higher in display-absent conditions than in conditions in which the display was accessible. Finally, SA was generally higher when the traffic display was present in the GCS. The lack of significant differences in objective performance could be attributable to two factors. First, separation authority was with ATC across both display conditions, so the inclusion of the display did not offer information to RPICs that supports a task for which they were responsible. Second, the simple inclusion of traffic information (absent conflict alerting and/or maneuver recommendations) increases the LOA only at the information acquisition and information analysis phases of processing. Onnasch et al. (2014) reported that automation at the later stages of processing (i.e., decision and action selection and action implementation) could be considered "more automation" than automation at the earlier stages of processing (i.e., information acquisition and information analysis). Therefore, it is possible that the LOA simply was not a high enough degree of automation to influence the objective performance measures. However, the increased SA associated with the inclusion of the display cannot be overlooked, as SA is essential for interacting with the automation and, consequently, effective system performance (Durso et al., 2014).

In another DAA human-in-the-loop experiment, Pack, Draper, Darrah, Squire, and Cooks (2015) tested five DAA display configurations on RPIC reliance on maneuver automation, RT to alerts, and number of collision avoidance alerts. The five display types included: (1) *informative basic*, which provided ownship location on a moving map display, intruder alert level, intruder relative altitude, intruder history trails, and intruder vertical velocity up/down arrows; (2) *informative advanced*, which provided *informative basic* information plus a collision avoidance ring around ownship, 30-second predictive heading lines for intruder and ownship, vertical situation display, closest point of approach (CPA) indications, time-to-CPA, and predictive collision avoidance alerting; (3) *text display*, which included *informative basic* information plus a text-based recommended maneuver; (4) *vector display*, which included the *text display* information plus depiction of the resolution vector; and (5) *banding display*, which included the *text display* information plus continuous display of an arc showing the RPIC areas of acceptable maneuvering. These five display types represented three levels of DAA decision and action selection manipulation, including none (*informative basic*), assisted option generation (*informative advanced*), and management by consent (*text display*, *vector display*, and *banding display*). Results revealed generally little difference among the display types on the objective dependent variables. The *banding display* resulted in approximately 3-second faster RT than the remaining four displays, but this difference did not reach statistical significance. The *banding display* also generally received highest subjective preference scores. The results suggest that a DAA LOA of assisted option generation in combination with management by consent, as were presented on the banding display, may yield the best information set in terms of safe DAA performance.

Another experiment assessing the effects of DAA display information was reported in three papers (Fern, Rorie, Pack, Shively, & Draper, 2015; Monk, Shively, Fern, & Rorie, 2015; Santiago &

Mueller, 2015). In the experiment, pilots were asked to fly two pre-planned routes, using the display to self-separate from intruder aircraft while responding to scripted vehicle health and status queries. The authors specify that participants conducted *fire line* and *coastal watch* missions while flying through Oakland Center airspace; however, there was no indication across the three papers that participants were required to devote any attentional or cognitive resources to one of these missions. Therefore, this study was considered to contribute to DAA in the en route phase of flight rather than in the aerial work phase of flight. Two levels of DAA display information were presented to RPICs, including a *basic* and *advanced* display, representing decision and action selection automation at levels of none and management by consent, respectively. These displays were informed by the work reported in Draper, Pack, Darrah, Moulton, and Calhoun (2014), using survey responses to identify the features to be used in the two display conditions. The *basic* display included intruder location, speed, relative altitude, vertical velocity, heading, flight ID, range, bearing, and color-coded traffic alert, while the *advanced* display contained all of the basic information plus specialized alerting on traffic predicted to cause loss-of-well-clear, graphical depiction of CPA, time-to-CPA, a trial planner tool, and maneuver recommendations. Fern et al. (2015) reported *measured response* results, which are pilot RTs at eight discrete and operationally-relevant stages of pilot self-separation. They reported that total RT, defined as the time elapsed from initial traffic display alert to upload of the final resolution maneuver, was 13.79 seconds longer with the *basic* information displays than with the *advanced* information displays, a statistically significant difference. Similarly, the total edit time (defined as the time required for the pilot to develop a suitable resolution maneuver) was significantly longer for the *basic* display condition than for the *advanced* display condition, a difference of 8.94 seconds. Santiago and Mueller (2015) reported a 45% reduction in losses of well clear for the *advanced* display compared to the *basic* display, but this difference was not statistically significant. Finally, Monk et al. (2015) revealed pilot preferences for the advanced display, particularly when integrated with the moving-map (i.e., not a stand-alone display). However, the advanced information yielded higher subjective ratings of display clutter. Overall, the results of the experiment emphasize the usefulness of the *advanced* display information.

In a follow-on effort, Rorie and Fern (2015) and Santiago and Mueller (2015) reported a human-in-the-loop experiment with the objective of identifying which specific information features in the *advanced* display configuration in the previous experiment were most beneficial to RPICs. Similar to the previous experiment, participants flew one of two missions in Oakland Center airspace during which they were required to coordinate with ATC to avoid intruder traffic, while also responding to UAS health and status queries. Again, it should be noted that the authors specify that two missions were conducted in Oakland Center airspace, but the “missions” did not require any RPIC attentional or cognitive resources beyond those of en route flight. Four display types contained the *basic* information from the previous experiment as a baseline display; the four display types represented a full crossing of the trial planner tool (decision and action selection LOA of assisted option generation) and a recommended maneuver (decision and action selection LOA of management by consent). Rorie and Fern (2015), who reported the *measured response* RTs, revealed initial maneuver edit time, total maneuver edit time, and total RT to be significantly shorter for displays containing the recommended maneuver. Similarly, Santiago and Mueller (2015) revealed fewer losses of well clear with the displays containing the maneuver recommendation functionality, but analysis of variance (ANOVA) revealed a lack of statistical differences among the displays. Across both experiments, the results suggest that presenting the

RPIC with a maneuver option (management by consent) enhances the RPIC's ability to successfully perform the DAA task than automation assisting the RPIC in generating potential avoidance maneuvers (assisted option generation). This is consistent with the conclusions made by Kirlik (1993) and Parasuraman and Riley (1997), who emphasized minimizing time and effort costs of engaging automation to complete a task.

Using a systems engineering approach to human-automation function allocation, Lee and Mueller (2013) reported a method to explore a range of human-automation function allocation strategies for UAS, focusing on the DAA task. The work began with a multi-dimensional concept map, and used the results to inform a functional decomposition and allocation procedure. As an application of the method, the authors provided results for UAS function allocation strategies in an environment where the UAV is being monitored by ATC. In general, their function allocation results suggest that ATC will shoulder a lot of the workload associated with the DAA task, but the UAS RPIC requires automated capabilities to satisfy the NAS see-and-avoid requirements (Federal Aviation Administration, 2013). When separation assurance has been delegated to the UAS RPIC, Lee and Mueller suggest that the system should not be fully autonomous; i.e., the RPIC should have at least veto power over the automation. This reflects a decision and action selection LOA of management by exception or lower. The recommendations match the envisioned future operation of UAS in the NAS, which will not allow fully autonomous vehicles (Davis, 2008; Federal Aviation Administration, 2012).

3.4.3.3 Summary of Literature in the En Route Phase of Flight

Nullmeyer, Montijo, Herz, and Leonik (2007) report a large proportion of Predator UAS mishaps occur in the en route phase of flight, with a large portion resulting from human error. This highlights the importance of sound automation strategies in this phase of flight, as many operations will require a large proportion of total flight time allocated to the en route phase. Regarding vehicle control during the en route phase of UAS flight, the use of vector control and waypoint control are promising alternatives for control automation (Williams, 2012). In addition to this, the results reported by Calhoun et al. (2013) suggest that RPICs prefer the freedom to freely switch between a variety of control modes; this has been termed *adaptable automation* in the human-automation interaction field, leaving the RPIC with the authority to decide what LOA (s)he uses (Miller & Parasuraman, 2007). The DAA literature corroborates this premise, as some work revealed that higher LOAs did not necessarily translate to lower RT to intruder collisions, since the time to engage the higher LOA was longer than for the lower LOA (Santiago & Mueller, 2015). Regarding DAA functionality, the literature generally indicates that information automation alone (e.g., conflict alerting) may not be sufficient for assisting RPICs in the DAA task. Prior research has indicated that a minimum of 14-16 seconds upon collision detection is required for a UAS pilot to successfully maneuver his/her aircraft to avoid a collision (Hardman, Colombi, Jacques, Hill, & Miller, 2009; Santiago & Mueller, 2015). Generating a successful maneuver can be a difficult, resource-consuming process for an RPIC, as there are many constraints to be accounted for. Therefore, in order to meet this the requirements of successful maneuver generation in a sufficient amount of time, automation should, at the very least, provide salient cues on maneuvers or areas that are not sufficient for avoidance (e.g., the banding display reported by Pack et al. (2015)) or provide maneuver suggestions to the RPIC. Related to this, Billings (1996), Bainbridge (1983), and Parasuraman et al. (2000) stress the importance of automating tasks with completion times that human operators cannot reliably achieve.

3.4.4 Aerial Work

The work included in this section includes phases of flight during which the participant is performing a mission or aerial work, demanding attentional and/or cognitive resources, while simultaneously operating the UAS.

3.4.4.1 Vehicle Control

In an experiment assessing flight control LOAs, Rorie and Fern (2014) manipulated three levels of control automation to assess the effect on pilot ability to comply with ATC traffic clearances while flying a pre-planned gridded pattern. The three LOAs implemented, which represented varying levels of action implementation automation, were manual *stick-and-throttle*, *waypoint editing*, and *autopilot*. In the *stick-and-throttle* condition, lateral and vertical maneuvers were achievable through joystick movements. In the *waypoint editing* condition, lateral and vertical maneuvers were made via editing waypoints on a navigation display interface. In the *auto-pilot* condition, pilots monitored the aircraft and were able to override the automation via altitude and heading holds. Dependent variables included *measured response* RTs, which are measures of the amount of time required to complete difference phases of the maneuver selection and implementation task. For the overall time to receive, plan, and complete an avoidance maneuver, the manual stick-and-throttle interface led to the shortest RT, followed by the auto-pilot mode, followed by the waypoint editing mode. The source of the differences was the fact that participants were able to generate successful maneuvers on the first attempt with the stick-and-throttle and autopilot modes, but the operators using the waypoint editing interface often needed multiple attempts to implement a successful maneuver. Therefore, although the waypoint editing was a higher level of control automation than the stick-and-throttle interface (action implementation: compulsory feedback vs. none), performance was significantly degraded. This reflects the results reported by Kirlik (1993), who stated that high automation engagement effort may dissuade participants from using automation in favor of manual control.

Over two similar experiments, Wickens and colleagues assessed the effects of two different forms of RPIC control automation for an image inspection task (Dixon et al., 2005; Wickens & Dixon, 2002; Wickens, Dixon, & Chang, 2003). In both experiments, participants were asked to fly to specific waypoints where they inspected payload video and reported targets seen at each location. When traveling between locations, there were camouflaged targets that participants were asked to search for and identify. Two forms of automation were manipulated in both experiments. In the *baseline* condition, participants controlled the aircraft via joystick, and in the *autopilot* condition, participants entered destination coordinates via keyboard and the aircraft automatically flew to that location (system status alerting automation was also manipulated, described in Section 3.4.4.3). The manipulation of control automation corresponded to decision and action selection and action implementation LOAs of none in the *baseline* condition, and fully automated decision selection and compulsory feedback, respectively, in the *autopilot* condition. In the first experiment, Wickens and Dixon (2002), the *autopilot* condition yielded more accurate failure detection rates and target detection rates, as well as a significant reduction in flight error (as expected, since control was fully automated). The second experiment, reported in Wickens, Dixon, et al. (2003) and Dixon et al. (2005), differed from the first in that it included a two-UAV condition and provided experiment participants with a performance incentive to increase participant motivation. Within the single-UAV condition, there was a significant effect of control level such that the *autopilot* condition yielded smaller tracking error, decreased number of repeat requests for information, larger secondary target detection rate, and smaller system failure detection time. There was no significant effect of control level on primary target report time, primary target report accuracy, secondary target report time, system failure detection rate, or system failure report accuracy. In general, the *autopilot* condition reduced the resources required by the RPIC, benefiting all of the tasks the RPIC in which the RPIC was engaged (vehicle control, target search, system status monitoring, etc.). Across the two experiments, participants seemed to prioritize tasks in the following order: (1) flight control, (2) primary mission success, (3) system health, and (4) secondary mission success. Pilots tended to exhibit behavior protecting the higher-priority tasks, so they were less impacted by the automation levels than the lower-priority tasks.

3.4.4.2 Detect and Avoid

Kenny, Shively, and Jordan (2014) conducted a human-in-the-loop experiment assessing the effects of two levels of conflict alerting on various objective and subjective measures while conducting a CO_2 monitoring task in Los Angeles Center airspace. The mission objectives were to follow the pre-planned route, reroute in response to mission messages, reroute to maintain separation from intruder aircraft, and maintain communication with ATC as necessary. The two conflict alerting levels included (1) a *basic* level, which displayed intruder call sign, altitude, airspeed, and color denoting relative altitude (an information analysis LOA of automated situation assessment); and (2) a *conflict alerting* level, which included the *basic* information plus visual and aural conflict detection alerts (an information analysis LOA of automated situation assessment and reference generation with alerting). There was no significant effect of conflict alerting on number of losses of separation, in-flight workload probes, post-flight NASA-TLX ratings, or post-flight subjective SA ratings. However, the alerting yielded significantly higher accuracy to in-flight SA probe responses (a more objective measure of SA than post-flight self-ratings), and usability ratings revealed preference for the alerting display. While the UAS pilots preferred the alerting functionality, the objective measures suggest alerting alone has little influence on pilot DAA performance. It is possible that conflict alerting is not a high enough LOA to support pilot ability to successfully reroute in response to intruders.

Building on their previous UAS DAA work, Rorie, Fern, and Shively (2016) conducted a human-in-the-loop experiment to assess DAA displays containing suggestive maneuver guidance, providing a range of acceptable heading and altitude values yielding safe separation (as opposed to directive guidance, which explicitly provides a maneuver suggestion). Four display types were presented to the RPIC, representing varying levels of decision and action selection LOAs. The *baseline* display provided pilots with standard intruder information (location, bearing, heading, etc.) and conflict alerting, representing a decision and action selection LOA of none. The *no fly bands* display included the *baseline* information as well as horizontal and vertical suggestive maneuver guidance via amber-colored bands reflecting the alert associated with that heading and altitude (similar to the *banding* display used by Pack et al. (2015)). The *omni bands* display was similar to the no fly bands display, but included several differences, including (a) alerting that accounted for ownship intent; (b) vertical guidance applied to absolute headings rather than relative headings; and (c) multiple colors to reflect alert levels. Finally, the *vector planning tools* display required the pilot to engage a horizontal or vertical planning tool via a click-and-drag interface; the DAA automation gave feedback as to whether the pilot-generated route avoided intruders. The latter three display types represented a decision and action selection LOA of assisted option generation. Participants flew two different missions, using the display to maneuver (and coordinate plans with ATC) around intruders while simultaneously responding to scripted UAS health and status tasks. Dependent variables recorded included *measured response* RT values, maneuver type, maneuver efficiency (measured in degrees off of the planned path), and encounters containing multiple maneuver uploads. The banding conditions required less time to respond to an alert and implement a maneuver than the other two conditions. Pilots overwhelmingly preferred lateral maneuvers, but this did not vary across display types, and the baseline condition yielded less efficient maneuvers (i.e., larger angle off the planned path) than the three remaining conditions. Finally, the baseline display yielded more instances of multiple maneuver uploads than the remaining display types. These results corroborate Kirlik's (1993) findings regarding the effort required for automation engagement versus the potential benefits. While the vector planning display was at a similar LOA as the banding displays, the longer engagement time made performance with it worse for the objective measures than the banding displays. The results suggest that banding displays could be a promising option for DAA display design and LOA.

Using a task similar to an infrastructure inspection task, Lam, Mulder, and van Paassen (2007) assessed the effect of haptic force feedback on the control joystick to prevent UAV collisions with buildings. The authors compared UAS operation with haptic feedback from two algorithms (both considered a decision and option selection LOA of assisted option generation) with a no-haptic-feedback condition (considered a fully manual level of decision and action selection automation). In the experiment, participants flew three simulated trials, each containing six subtasks requiring pilots to negotiate different structure configurations (e.g., fly the UAV between two structures, fly around a structure with the smallest turn radius possible, etc.). Dependent variables recorded included the number of collisions, time required to complete each subtask, various speed-related measures, minimum distance to an obstacle, time spent within a critical distance of an obstacle, standard deviation of hand moment on the joystick, and workload measured via NASA-TLX. The haptic feedback conditions resulted in fewer collisions and less time within a critical distance to obstacles, but results were mixed for task completion time, minimum distance from obstacles, and the speed-related measures. Furthermore, the haptic conditions led to significantly higher NASA-TLX ratings than the no haptic feedback condition. While the haptic feedback was successful in keeping the UAV away from obstacles, it is possible that the haptic implementation of the automation was so restrictive that it led to mixed results overall. Billings (1996) suggests that it may not be good practice to impose hard performance envelope limits on pilots, since there could be cases where the pilot needs to exceed those limits to ensure safety of the aircraft. Rather, Billings suggests soft envelope limits. The haptic feedback conditions tested by Lam et al. (2007) essentially removed the flight control authority from the RPIC, likely leading to the mixed results.

3.4.4.3 System Health and Status Monitoring

Over two experiments, Wickens and colleagues assessed the effects of two different forms of automation on RPIC control, image inspection, and system health monitoring performance (Dixon et al., 2005; Wickens & Dixon, 2002; Wickens, Dixon, et al., 2003). Described in more detail in Section 3.4.4.1, participants in both experiments were required to search for secondary targets while flying from one primary target to the next, while simultaneously monitoring system health and status. In the *baseline* condition, there was no alerting of abnormal system states (only visual presentation via gauges). In the *auditory* condition, there was auditory presentation of instructions and auditory alerting of system failures. Level of control automation was also manipulated, but not used in combination with the *auditory* condition. The manipulation of alerting corresponded to an information analysis LOA of none in the *baseline* condition, and automated situation assessment and reference generation with alerting in the *auditory* condition. In the first experiment, Wickens and Dixon (2002) reported that the auditory alerting condition led to increased failure detection rate and shorter system failure RT, as well as increased target detection rates. Within the single-UAV condition in the second experiment (Dixon et al., 2005; Wickens, Dixon, et al., 2003), the aural alerts significantly improved system failure detection and memory of task instructions (i.e., performance in tasks that were presented aurally); the *auditory* condition had no carry-over effect to the image inspection or flight control tasks, unlike the higher level of control automation, which freed RPIC resources to facilitate performance in other tasks.

In another human-in-the-loop simulation experiment assessing system health and status automation during a simulated target acquisition task, Ruff, Narayanan, and Draper (2002) provided RPICs with three decision and action selection LOAs for various UAS conditions. These conditions include low fuel, UAV approaching stall speed, UAV approaching minimum or maximum altitude, target detection, if the UAV is within weapon firing range, whether a target has been destroyed, and when all waypoints have been visited. In the *manual* condition, participants were required to operate the UAS without the assistance of automation; in the *management by consent* condition, a pop-up dialog gave the participant an action recommendation; and in the *management by exception* condition, a dialog gave the participant an action recommendation, then executed it automatically after three seconds if the RPIC did not respond. Also manipulated in the experiment was decision aid fidelity (95% vs. 100% accuracy), and the number of UAVs operated (1, 2, and 4; the results presented here are only those that were evident in the single-UAV conditions). In general, the *management by consent* strategy yielded highest proportion of targets destroyed as well as the highest rate of recognition of incorrect decision aids. These performance measures suggest that participants were over-reliant on automation in the *management by exception* condition, whereas they were able to ensure the decision aid was correct before executing the action in the *management by consent* conditions. However, NASA-TLX ratings revealed RPIC workload to be higher for *management by consent* than for the *manual* condition, although the differences among the three levels are small (despite their significance). *Management by consent* did yield the highest SA ratings, followed by the *manual* condition, followed by *management by exception*. Taken together, the *management by consent* strategy reduced overreliance on automation and facilitated RPIC SA without increasing workload to an unmanageable level under single-UAV operation.

Van Dijk and De Reus (2010) conducted a human-in-the-loop experiment in which a pilot and mission commander conducted a target search mission under manipulation of two alerting LOAs. During a mission, there were times when the engine temperature became too hot and times when fuel level became low. In the *no alerting* condition, there was no alerting of this condition (reflecting an information analysis LOA of automated situation assessment). In the *alerting* condition, the RPIC received a visual alert just after onset of the high temperature or low fuel (reflecting an information analysis LOA of automated situation assessment and reference generation with alerting). Dependent variables included pilot NASA-TLX workload, SA, and detection accuracy of the engine temperature and fuel level conditions. Also manipulated was the number of UAVs operated (one, two, three, and four) in a supervisory control paradigm, but the results reported here concern only the single-UAV condition. There was no significant effect of automation level on any of the three dependent variables, counter to the findings of Wickens, Dixon, and colleagues (2005; 2002; 2003), who used auditory alerting of system status in a similar target search task. Williams (2007) suggests that alerts should take advantage of non-visual modalities, such as auditory or haptic; perhaps the difference in alert modality between the studies led to the difference in system status recognition performance. It is also possible that the lack of statistical differences reported by Van Dijk and De Reus is due to the fact that taskload was distributed across two crewmembers, leaving ample attentional resources available for monitoring system status.

Using a three-stage paradigm that did not include a human-in-the-loop simulation, Cook and Smallman (2013) used structured UAS SME interviews to define tasks and roles, allocate tasks to humans and automation, and define communication requirements among agents for current and future UAS operations. The tasks were focused on detecting and responding to problems and changes rather than simply monitoring situations. In the first stage, a task analysis was conducted with UAS SMEs resulting in monitoring tasks for the vehicle, environment, sensors, team, and mission. These tasks were defined for the *detect*, *assess*, and *decide* stages of information processing. Next, SMEs assigned LOAs to each task (reflecting current-day operations) using the following taxonomy: (1) fully human, (2) human delegated, (3) human supervised or management by consent, (4) nearly autonomous or management by exception, and (5) fully autonomous. Next, SMEs used this taxonomy to suggest LOAs for future UAS operations. Generally, almost all current operations are either fully human or human delegated, while future envisioned systems will be mostly human supervised, nearly autonomous, or fully autonomous. A common comment during the interviews about current-day UAS automation was that SMEs anticipated needing more human involvement for tasks relating to deciding on a course of action, as well as more human involvement or approval as mission criticality increased. Finally, the third stage of the analysis revealed current displays to promote reactive monitoring, whereas future displays should promote proactive monitoring. Overall, the SME feedback suggests that future UASs will be designed with a high LOA. Their comments emphasized the importance of the RPIC remaining involved in decision making, suggesting their inherent need to maintain adequate SA in case an anomaly required human intervention.

Stanard, Bearden, and Rothwell (2013) utilized a think-aloud verbal protocol paradigm for SMEs conducting the necessary tasks to surveil a *VIP vehicle* traveling from an origin to a destination. The task was a four-UAV monitoring task, but since the task was a discrete-event “table-top” exercise (i.e., there was no human-in-the-loop simulation of the tasks), the results are applicable to single-UAV function allocation. Post-experiment discussions with the SMEs revealed three main points about automation assistance. First, SMEs emphasized that automation should keep track of simple calculations and other information that requires cognitive resources, such as assessing whether UAV characteristics are capable of performing a task, or time/distance calculations between UAVs and locations (i.e., automation at the information analysis stage of information processing). This recommendation supports prior literature in the human-automation interaction domain (Endsley & Kiris, 1995). Second, the SMEs suggested that automation should provide one or more decision and action selection options to the RPIC, who has the authority to make the final decision. The third point made by SMEs was that automation should be allowed to adapt to RPIC constraints (i.e., a mixed initiative approach).

3.4.4.4 Path Re-planning

Cook, Smallman, Lacson, and Manes (2010) conducted a human-in-the-loop experiment in which participants were required to perform a military reconnaissance task while re-planning to avoid airspaces changing between restricted and unrestricted. Three display types were presented to the RPICs, one reflecting a restricted airspace information analysis LOA of automated reference generation (i.e., only textual presentation of restricted airspaces) while the two treatment display types pictorially presented the restricted airspace on the moving-map display, reflecting an information analysis automation LOA of automated situation assessment and reference generation. In general, the displays reflecting the LOA of automated situation assessment yielded higher performance across the dependent variables, including route re-planning time, re-planning error rate, and error severity (a measure of the number of restricted airspace violations). Overall, the results suggest that the overlay of restricted airspace information on the navigation display is beneficial for path re-planning. However, the experiment did not require participants to monitor aircraft status or intruder aircraft, which may detract from the realism of the study or the applicability of the results to UAS operation in the NAS.

In a human-in-the-loop simulation of one- and three-UAV supervisory control, Calhoun, Draper, and Ruff (2009) assessed the effect of three LOAs in a re-routing task (in response to the appearance of airborne and ground-based threats) while participants simultaneously conducted an image analysis task and monitored system health and status. In the lowest LOA, two alternate re-routes were suggested to the RPIC; in the intermediate LOA, one alternate re-route was suggested, and in the highest LOA, a re-route option was selected by the automation and the RPIC was given five seconds to accept or reject it before it was implemented. The corresponding decision and action selection LOAs were filtered option generation, management by consent, and management by exception for the low, intermediate, and high levels, respectively. In two out of the six re-routing tasks within a trial, the suggested route was not adequate for avoiding the threat, requiring participants to validate automation accuracy. The results revealed that it took significantly more time to complete the re-route task when RPICs used the high LOA, compared to the intermediate and low conditions. The LOA condition had no significant effect on secondary task performance, including responses to unidentified aircraft, health and status alerts, and image analysis. Despite the performance decrements associated with the management by exception LOA, RPICs rated their abilities to be highest when using the management by exception LOA. The performance decrement with the management by exception LOA was attributed to the need for RPICs to ensure that the recommended flight path was valid, emphasizing the potential negative side effects of a management by exception approach combined with imperfect automation, a finding also reported by Ruff et al. (2002).

In a nine-UAV supervisory control paradigm, Prinet, Terhune, and Sarter (2012) manipulated three path re-planning LOAs and two levels of workload. Participants, in a military target search and identification task, were required to re-plan UAV paths due to the addition/removal of a target, activation of no-fly zones, poor weather conditions, or a UAV fuel leak. The three decision and action selection LOAs included *manual*, for which participants used the drag-and-drop interface to re-plan UAV routes (reflecting a LOA of manual); *intermediate*, for which automation suggested three alternative routes (reflecting a level of filtered option generation); and *high*, for which the automation suggested one alternative and the RPIC could accept or reject it (reflecting a LOA of management by consent). The *high* LOA condition yielded the fastest re-plan completion time, highest re-planning score (a measure of the quality of the re-planned route), and highest number of UAVs shot down by enemy weapons. The *intermediate* level followed for the three dependent variables, followed by the *manual* condition. There was no significant difference in target detection accuracy between the fully *high* and *intermediate* LOAs, but both yielded significantly higher target identification accuracy than the *manual* condition. Subjective perceptions revealed that *high* automation was most helpful of the three levels during periods of high workload, but there were no significant differences in subjective workload ratings among the three LOAs. With the caveat that this work was a nine-UAV supervisory control task, the results yield similar conclusions to the detect-and-avoid literature; namely, that automation should provide re-route options to the participants. This reiterates the fact that generating a trajectory that meets all environmental constraints, when done concurrently with the demands associated with successfully operating a UAS, imposes high workload on the RPIC, necessitating higher levels of decision and action selection automation.

3.4.4.5 Communication

There is a paucity of literature in RPIC communication, but results and recommendations reported by Cummings (2004) in a Navy Tactical Tomahawk missile monitoring human-in-the-loop experiment are applicable to communication in a UAS context. In her experiment, Cummings revealed that participants exhibited unexpected behavior—they tended to fixate on the chat client interface (on which participants sent and received text-based messages to other crew members) to the detriment of monitoring missile progress, despite the fact that RPICs were told to prioritize the missile monitoring task. Correlation analyses revealed that participants who devoted too much attention to the chat window performed worse in the missile-monitoring task. Referring to the related interruption literature, Cummings revealed potential issues with chat messages being received at times of high RPIC workload, negative affecting performance in the primary task. For this reason, it was recommended that adaptive interfaces be used that intelligently manage incoming messages, reflecting an information analysis LOA of automated situation assessment and reference generation, and a decision and action selection LOA of management by exception or fully automated decision selection. However, as is the case with any automation decision in critical systems, the author cautioned that work needs to be done to ensure there are no unintended consequences of such automation.

3.4.4.6 Transfer of Control

Transfer of control is a unique aspect of UAS operation; since the crew is not onboard the aircraft, control can be transferred between RPICs within the same control station, between crews at different control stations, or between members of the same crew (Tvaryanas, 2006). Williams (2006) revealed through a military UAS accident analysis that a common theme across mishaps is the lack of awareness of system settings on the part of the receiving crew. Since this is a new aspect of aviation, there is little work assessing the automation necessary to ensure reliable transfer of control.

In one human-in-the-loop experiment, Fern and Shively (2011) assessed the effect of four display designs (spanning two information analysis LOAs) on an RPIC's ability to effectively receive control of a UAS. Participants were given control of a UAV already in flight, and were required to use the information display to obtain knowledge about the planned route and cleared waypoints in as little time as possible. The four display formats included a *baseline* display (requiring participants to read through chat history to assess the state of the UAS), a *text* display (presenting textual information about the state of the UAS), a *graphics* display (providing a map containing relevant information about UAS status), and a *map* display (relevant information overlaid on the tactical situation display, which contained a moving map and route/waypoint information). The *baseline* display reflected an information analysis LOA of none, while the remaining three reflected an information analysis LOA of automated situation assessment. The results of the experiment revealed that time to determine airspace status was significantly shorter in the *text* and *graphics* displays than in the *baseline* chat history display, but there were no significant differences among the display types on time spent on each mission. Similarly, the *baseline* display yielded significantly lower SA than the three remaining displays, with no statistical differences among the *text*, *graphics*, and *map* displays. Similar trends were exhibited for subjective ratings of usefulness, ease of use, and workload. The *map* overlay display was ranked as the most preferred display, followed by the *graphics* display, the *text* display, and the *baseline* display. Despite the multiple display formats used, there was a trend of better performance and higher SA for the displays utilizing the higher information analysis LOA.

3.4.4.7 Summary of Literature in the Aerial Work Phase of Flight

The results of Wickens, Dixon, and colleagues (2005; 2002; 2003) suggest that vehicle control automation has the potential to benefit UAS RPIC tasks beyond vehicle control. Since UAS RPICs tended to prioritize vehicle control over other secondary tasks, automation of control frees RPIC resources to devote to secondary tasks (e.g., system health, communication, payload operation, etc.). Furthermore, the results reported by Rorie and Fern (2014) reiterate the fact that level of control automation alone does not necessarily lead to better performance; care needs to be taken to ensure that the automation engagement costs do not degrade RPIC performance (Kirlik, 1993; Parasuraman & Riley, 1997). This conclusion was also prevalent in the DAA literature, as elaborated in the en route phase of flight (Section 3.4.3.2). One trend that emerged from the DAA and re-planning literature was that management by consent automation tended to yield better performance across UAS tasks than management by exception, despite the fact that management by exception is generally considered to be the higher LOA (Parasuraman et al., 2000). This was particularly the case when the experiments utilized imperfect automation (Calhoun et al., 2009; Ruff et al., 2002), which is a relevant consideration for UAS operation in the NAS since a flawless LOA is difficult to obtain. Finally, the literature in RPIC communication and transfer of control is lacking, but Cummings (2004) warns that text-based chat clients could be disruptive to UAS operations, while Fern and Shively (2011) concluded that current-day operations of requiring UAS crews receiving control to sift through chat histories to ascertain current UAS and mission status is not sufficient for future UAS operation in the NAS.

3.4.5 Approach and Landing

In their discrete event simulation, Barnes et al. (2000) revealed the tasks of *monitor landing* and *modify landing* to be candidates for automation since they both require three or more steps to perform properly. Similarly, Williams (2004) revealed that UASs requiring an EP to perform landing procedures had much higher mishap rates than those for which either the internal pilot performed the procedure, or the landing procedure was fully automated. A similar finding was reported in an accident analysis conducted by Rash, LeDuc, and Manning (2006), who revealed that human error in UAS operations occurs most often in the difficult phases of flight, such as takeoffs and landings. This suggests that a high LOA may be beneficial for conducting approach and landing procedures.

Discussed previously in Section 3.4.2, De Vries et al. (2006) conducted two human-in-the-loop experiments assessing three LOAs of intruder detection automation and terrain detection automation on operator UAS approaches. RPICs were frequently able to detect conflicts before the automated warning system, allowing them to institute resolution maneuvers before receiving automated maneuver suggestions. When this was the case, RPICs struggled to formulate a successful maneuver, suggesting that information analysis automation may not be sufficient for conflict avoidance, especially in workload-intensive phases of flight like departure and approach.

An earlier human-in-the-loop experiment assessed the effects of haptic and visual alerting on pilot subjective perceptions of SA, workload, and performance for a UAV approach in the presence of turbulence (Ruff, Draper, Lu, Poole, & Repperger, 2000). The experimenters manipulated four variables, including the presence/absence of turbulence alerting, two levels of turbulence direction, two levels of turbulence severity, and distance from the runway at turbulence onset (near vs. far). In the *turbulence alerting* condition, participants were exposed to haptic feedback on the joystick reflecting the direction and strength of turbulence as well as a visual alert. The *baseline* conditions contained neither alerting modality. The alerting levels reflect information analysis automation of automated situation assessment and reference generation with alerting, and none, respectively. The results revealed that SA ratings were higher for the *turbulence alerting* condition than for the *baseline* condition, and an interaction effect revealed greater facilitation of SA during the alerting conditions, particularly when the aircraft was further from the runway at turbulence onset. Participants rated landing difficulty to increase under the alerting condition compared to the baseline condition, but only three out of the five participants preferred the haptic feedback condition. In general, the results suggest that RPIC perceptions of the haptic feedback were underwhelming, which may be attributed to the fact that the haptic cues may have limited or disrupted RPIC ability to control the vehicle, despite the fact that self-reported SA increased with the inclusion of the alerting condition. The results corroborate the conclusions of Lam et al. (2007), who also reported generally negative effects of haptic feedback through the control device.

3.4.5.1 Summary of Literature in the Approach and Landing Phases of Flight

Similar to the literature on the takeoff and departure phases of flight, accident analyses suggest that UASs should have relatively high LOAs in the approach and landing phases of flight, as they are associated with high levels of workload (Williams, 2004). The findings of De Vries et al. (2006) suggest that RPICs require automation assistance to avoid intruder and terrain conflicts while approaching the runway, while Ruff et al. (2000) suggest that a haptic turbulence alerting system may not be ideal for pilots. However, visual and/or auditory alerting of turbulence could be beneficial for pilots during the approach phase of flight. Overall, there is not much literature on the approach and landing phases of UAS operation, making it an area worth investigation for researchers in the future.

3.5 RESEARCH GAP ANALYSIS

This section explicitly identifies research gaps in the UAS human-automation function allocation literature, based on the document taxonomy categorizations presented in Section 3.3. The sections are organized by the major taxonomy categories (e.g., function allocation strategy, measures, etc.). The percentages presented in this section are followed by a fraction, where the numerator is the number of papers represented by the specified subcategory and the denominator represents the total number of papers in that subcategory's parent category.

3.5.1 Function Allocation Strategy

Generally, much less work focuses on automation in the information acquisition stage of processing than the other three stages, with the information acquisition stage of processing accounting for 9.59% (21/219) of the total categorizations, the information analysis stage accounting for 29.68% (65/219), the decision and action stage accounting for 35.62% (78/219), and the action implementation stage accounting for 25.11% (55/219). Within each LOA, however, there is little work on mixed initiative approaches to automation (i.e., the human operator setting constraints on the automation), with only 2.74% (6/219) of categorizations over all reviewed documents utilizing any form of mixed initiative automation across the four stages of information processing.

3.5.2 Measures

Most of the measures reported in the literature reviewed focused on human-automation interaction (36.96%; 34/92), mission performance (22.83%; 21/92), and control (19.57%; 18/92). Little work utilized function allocation measures (2.17%; 2/92), attention allocation measures (1.09%; 1/92), or subjective usability measures (4.35%; 4/92) to assess automation effectiveness. Although there were a large number of documents that used human-automation interaction measures, a great majority measured either workload (55.88%; 19/34) or SA (32.35%; 11/34). While these constructs are very important, much less work measured complacency (0.00%; 0/34), skill degradation (0.00%; 0/34), trust (5.88%; 2/34), or reliance (2.94%; 1/34) to assess automation strategies, which are also important aspects that influence RPIC performance.

3.5.3 Task

A majority of the literature reviewed for UAS human-automation function allocation was in the en route (16.28%; 7/43) or the aerial work/mission (53.49%; 23/43) phases of flight. There was substantially less literature in the takeoff (4.65%; 2/43), departure (6.98%; 3/43), descent (2.33%; 1/43), approach (9.30%; 4/43), and landing (4.65%; 2/43) phases of flight, and no documents reviewed assessed automation during UAS taxi.

Regarding generic UAS functions, *manage* (27.80%; 62/223), *aviate* (32.29%; 72/223), and *navigate* (26.46%; 59/223) are well-represented in the literature, with *communication* (13.45%; 30/223) much less represented. Within the *manage* function, planning and transfer of control are the most under-represented categories, at 11.29% (7/62) and 8.06% (5/62) of the *manage* function literature, respectively. In the *aviate* category, two under-represented functions include monitor and configure control station (4.17%; 3/72) as well as monitor and control the status of links

(5.56%; 4/72). Finally, within the navigate function, the tasks of ensuring lost link procedure remains appropriate (1.69%; 1/59) and terminating flight (1.69%; 1/59) represent significant gaps in the UAS human-automation function allocation literature.

For the aerial work/mission conducted, a majority of the existing literature requires RPICs to conduct military-related tasks (72.41%; 21/29), with only 27.59% (8/29) conducting civil UAS tasks, and zero documents using commercial missions. Future research should begin to utilize missions that are envisioned to be conducted in the NAS.

3.5.4 Environment

A small percentage (6.67%; 3/45) of the studies reviewed manipulated the atmospheric conditions. Intruder traffic was frequently included in the literature (71.11%; 32/45), and geography was included in 22.22% (10/45) of the literature categorizations. In all of the categorizations, intruder traffic consisted of manned aircraft, with none of the literature requiring multiple unmanned aircraft to maintain separation from each other. Generally, future work should assess the effects of piloting a UAV through various atmospheric conditions and/or in airspace containing a mix of manned and unmanned aircraft.

3.5.5 National Airspace Context

Only 22 of the documents reviewed explicitly stated the airspace used in their work; therefore, the categorizations in this section may not truly represent the research done in those airspace contexts. Regarding the airspace through which RPICs flew, there was a somewhat even distribution across Classes A, B, C, D, E, and G airspaces. Similar to the phase of flight categorizations in the Task section (Section 3.5.3), there is a dearth of literature on surface operations, evinced by the fact that zero out of the 22 categorizations were related to surface operations. Finally, 90% (9/10) categorizations were for IFR, while 10% (1/1) were for visual flight rules.

3.5.6 Participants/Crew

Regarding the pilot-in-command, 37.84% (14/37) categorizations specify that RPICs had manned aircraft experience; 24.32% (9/37) had experience operating a UAS, and 21.62% (8/37) had no experiencing operating an aircraft of any kind. Future work should continue to assess the effects of UAS automation on participants with manned and/or unmanned aircraft operational experience.

3.5.7 Control Station

Regarding hardware used to control the UAS, most control stations utilized either a desktop computer setup (50.00%; 13/26) or a suite of displays set up to replicate an actual control station (46.15%; 12/26). Only one study utilized a laptop computer (3.85%), and in that study, the laptop was used in conjunction with a desktop computer. Future work should assess the efficacy of using a laptop setup for controlling a UAS, which can be used as a contingency plan in case of control station failure.

In most of the studies, the RPIC had multiple control device options. A majority of the literature utilized point-and-click (42.86%; 21/49) and/or keyboard input (30.61%; 15/49), with fewer categorizations allowing direct control of the UAV via joystick (18.37%; 9/49) or stick-and-throttle (6.12%; 3/49). Two less-used control interfaces were touch screens (2.04%; 1/49) and knobs (0.00%; 0/49). Due to the flexibility and the reduced bandwidth required for signal transmission, mouse-and-keyboard interfaces may show the most promise for future UAS control devices, but as touch screen technology continues to advance, future work should investigate the potential of using touch screens for UAS control.

The most commonly used displays were out-window (12.50%; 16/128), moving map (19.53%; 25/128), system health and status (13.28%; 17/128), traffic information (11.72%; 15/128), communication client (10.94%; 14/128), and navigation displays (19.53%; 25/128), which each accounted for 10-20% of the 203 total categorizations. Lesser-used displays, which should be investigated more in future work, include weather information (2.34%; 3/128), payload status (4.69%; 6/128), vertical situation displays (3.91%; 5/128), electronic checklist displays (1.56%; 2/128) and horizontal situation indicators (0.00%; 0/128).

3.5.8 Ownship

Many documents (15.07%; 11/73) did not specify the type of aircraft used. Of those that did specify, the most-used UAV was the Predator B/Reaper (14.00%; 7/50). Generally, future work should aim to assess function allocation strategies in as many different UAVs as possible, as the differing flight dynamics and control station setups could be a mediating factor in the effectiveness of various UAS human-automation strategies.

3.5.9 Type of Study

The UAS human-automation function allocation literature reflected a variety of research approaches, including human factors design and evaluation of an existing system (19.59%; 19/97), human-in-the-loop simulation (27.84%; 27/97), literature review (25.77%; 25/97), and products of the systems engineering lifecycle (15.46%; 15/97). Within the human factors design and evaluation approaches, 47.37% (9/19) categorizations used task analyses and 31.58% (6/19) used SME interviews. A small percentage of the literature used observation (5.26%; 1/19), participant questionnaires (5.26%; 1/19), heuristic evaluation (0.00%; 0/19) and/or focus groups (0.00%; 0/19). Future work should utilize these human factors approaches for human-centered design and evaluation of UASs.

Two lesser-used approaches included accident data analyses (6.19%; 6/97), computational modeling (4.12%; 4/97), and field tests (1.03%; 1/97), which can be expected since the development and use of UASs are still in their early stages. With more UASs expected to be produced in the future, the number of field tests and accident analyses will almost surely increase. Once more human performance data is collected on RPIC responses to various function allocation strategies, computational modeling can be utilized more to test a wider range of automation concepts.

4. DISCUSSION

The Joint Planning and Development Office (2012) defined the establishment of acceptable LOAs for UAS in the NAS as one of its goals for UAS integration into the NAS. While there has been much work contributing to this goal, there is much work left to be conducted before UAS can reliably operate in the NAS. Future UAS operations will require the pilot to have control and decision authority over the vehicle (Davis, 2008; Federal Aviation Administration, 2012), so it is imperative that UAS functions be automated utilizing a human-systems interaction approach. The review presented in this document was conducted to further the goal of establishing LOAs for UAS operation in the NAS.

There exist constraints outside the scope of this review that should, at the very least, be mentioned, as they potentially affect UAS human-automation function allocation strategies. First, the review does not account for potential technology-based constraints on the implementation of automation. The bandwidth of the wireless link between the control station and the UAV provides a constraint; lower LOAs (i.e., manual control) require higher link bandwidth (McCarley & Wickens, 2005; Theunissen, Tadema, & Goossens, 2009). Related to this, delay between actions and vehicle receipt of commands can have a negative effect on pilots. Furthermore,, there is little work in the UAS literature assessing imperfect UAS automation, including requiring pilots to manually perform a UAS task upon automation failure. In a meta-analysis using studies outside UAS operation, Wickens, Li, Santamaria, Sebok, and Sarter (2010) revealed that increasing automation benefits performance and also reduces workload, but increasing benefits with higher automation are accompanied by increasing costs for imperfectly reliable automation. Another related consideration is operator trust in automation (Parasuraman & Riley, 1997). Although this issue was approached by the human-in-the-loop studies conducted by Ruff et al. (2002) and Calhoun et al. (2009), RPIC performance under varying levels of automation reliability needs to be considered in the design of any UAS system.

As part of the A7 project, future work will provide function allocation recommendations based on the documents reviewed. Using these recommendations for human-automation function allocation, the next step will be to conduct a literature review and develop recommendations for UAS control station minimum information requirements, as function allocation and interface design are tightly linked to each other (Tang & Zhang, 2013). Using the function allocation and control station recommendations, a review will be conducted to develop UAS crewmember training and certification recommendations. Human-automation function allocation is a critical step in developing training and certification requirements, as the skills required to operate a UAS can vary greatly based on the function allocation strategy employed. Relevant considerations for training include prior flight experience (Schreiber et al., 2002), personality differences (Chappelle, McDonald, & McMillan, 2011; Hunter & Burke, 2002; Schmidt & Hunter, 1998), operator candidate selection (Carretta, 2011), decision-making strategies (Clare, Maere, & Cummings, 2012; Kennedy, Taylor, Reade, & Yesavage, 2010; Klein, 2008), multitasking ability (Salomon, Ferraro, Petros, Bernhardt, & Rhyner, 2015), and risk perception (Hunter, 2002, 2005; Pauley, O'Hare, & Wiggins, 2008). Finally, the A7 work will conclude with a review on and subsequent recommendations for visual observer training and certification requirements.

Future work should also focus on the gaps in the literature specified by this review. In particular, there is little work assessing the effects of mixed initiative approaches to automation in UAS operation. Future work could assess RPIC ability to set status alerting thresholds or preferred maneuver types for the automation to consider. Regarding alerting, future work should focus on the design of alerting systems that supports proactive monitoring rather than reactive monitoring (Cook & Smallman, 2013), allowing the RPIC to engage in a situation early enough to closely monitor and take initiative as necessary. Alerting needs to not only attract the RPIC’s attention, but also facilitate quick and accurate assessment of the situation and account for potential brittleness in the automation design. A majority of the work in UAS human-automation function allocation has been in the en route or aerial work phases of flight; research in the future should assess automation of other, higher-workload phases of flight such as takeoff, departure, approach, and landing. Furthermore, UAS taxi automation should be assessed, as it may be difficult for a remote operator to taxi to and from the runway while avoiding other aircraft and obstacles. There should also be a larger focus of future research on events unique to unmanned flight, such as the transfer of UAS control, lost link procedures, and flight termination. Regarding measures to assess automation effectiveness, future work should take more of a systems approach to assessing UAS function allocation, utilizing the function allocation measures more frequently. Future work should also use RPIC attention allocation patterns to measure automation effectiveness. Eye tracking technologies can reveal whether the RPIC is overloaded by particular automation (or lack thereof), and can also give real-time non-intrusive indications of cognitive workload.

5. REFERENCES

Bainbridge, L. (1983). Ironies of automation. *Automatica, 19*(6), 775-779.

Balzer, W. K., Doherty, M. E., & O'Connor, R. (1989). Effects of cognitive feedback on performance. *Psychological Bulletin, 106*(3), 410.

Barnes, M. J., Knapp, B. G., Tillman, B. W., Walters, B. A., & Velicki, D. (2000). *Crew systems analysis of unmanned aerial vehicle (UAV) future job and tasking environments*. Retrieved from http://www.dtic.mil/dtic/tr/fulltext/u2/a374230.pdf

Bass, E. J., Ernst-Fortin, S. T., Small, R. L., & Hogans Jr, J. (2004). Architecture and development environment of a knowledge-based monitor that facilitate incremental knowledge-base development. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 34*(4), 441-449.

Bass, E. J., & Pritchett, A. R. (2008). Human-automated judge learning: A methodology for examining human interaction with information analysis automation. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 38*(4), 759-776.

Billings, C. E. (1996). Human-centered aviation automation: Principles and guidelines.

Bisantz, A. M., Kirlik, A., Gay, P., Phipps, D. A., Walker, N., & Fisk, A. D. (2000). Modeling and analysis of a dynamic judgment task using a lens model approach. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 30*(6), 605-616.

Brunswik, E. (1956). *Perception and the representative design of psychological experiments*: Univ of California Press.

Calhoun, G. L., Draper, M., Miller, C., Ruff, H., Breeden, C., & Hamell, J. (2013). *Adaptable automation interface for multi-unmanned aerial systems control: Preliminary usability evaluation*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Calhoun, G. L., Draper, M. H., & Ruff, H. A. (2009). *Effect of level of automation on unmanned aerial vehicle routing task*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Carretta, T. R. (2011). Pilot candidate selection method. *Aviation Psychology and Applied Human Factors*.

Chappelle, W., McDonald, K., & McMillan, K. (2011). *Important and critical psychological attributes of USAF MQ-1 Predator and MQ-9 Reaper pilots according to subject matter experts*. Retrieved from

Clare, A. S., Maere, P. C., & Cummings, M. L. (2012). Assessing operator strategies for real-time replanning of multiple unmanned vehicles. *Intelligent Decision Technologies, 6*(3), 221-231.

Cook, M. B., & Smallman, H. S. (2013). *Human-centered command and control of future autonomous systems*. Retrieved from http://www.dtic.mil/cgi-bin/GetTRDoc?Location=U2&doc=GetTRDoc.pdf&AD=ADA588335

Cook, M. B., Smallman, H. S., Lacson, F. C., & Manes, D. I. (2010). *Situation displays for dynamic UAV replanning: Intuitions and performance for display formats*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Cooksey, R. W. (1996). *Judgment analysis: Theory, methods, and applications*: Academic Press.

Cummings, M. L. (2004). The need for command and control instant message adaptive interfaces: Lessons learned from Tactical Tomahawk human-in-the-loop simulations. *CyberPsychology & Behavior, 7*(6), 653-661.

Cummings, M. L., Marquez, J. J., & Visser, M. (2007). *Shadow TUAV Single Operator Consolidation: Display Assessment*. Retrieved from http://hdl.handle.net/1721.1/46728

Davis, K. D. (2008). Unmanned Aircraft Systems Operations in the US National Airspace System. *Interim Operational Approval Guidance*, 08-01.

De Vries, M. F. L., Koeners, G. J. M., Roefs, F. D., Van Ginkel, H. T. A., & Theunissen, E. (2006). *Operator support for time-critical situations: Design and evaluation*. Paper presented at the 25th DASC Digital Avionics Systems Conference.

Dingus, T. A., McGehee, D. V., Manakkal, N., Jahns, S. K., Carney, C., & Hankey, J. M. (1997). Human factors field evaluation of automotive headway maintenance/collision warning devices. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 39*(2), 216-229.

Dixon, S. R., & Wickens, C. D. (2006). Automation reliability in unmanned aerial vehicle control: A reliance-compliance model of automation dependence in high workload. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 48*(3), 474-486.

Dixon, S. R., Wickens, C. D., & Chang, D. (2005). Mission control of multiple unmanned aerial vehicles: A workload analysis. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 47*(3), 479-487.

Draper, M. H., Pack, J. S., Darrah, S. J., Moulton, S. N., & Calhoun, G. L. (2014). *Human-machine interface development for common airborne sense and avoid program*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Durso, F. T., Stearman, E. J., Morrow, D. G., Mosier, K. L., Fischer, U., Pop, V. L., & Feigh, K. M. (2014). Exploring Relationships of Human-Automation Interaction Consequences on Pilots Uncovering Subsystems. *Human Factors, 57*(3), 397-406.

Endsley, M. R. (1995a). Measurement of situation awareness in dynamic systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 37*(1), 65-84.

Endsley, M. R. (1995b). Toward a theory of situation awareness in dynamic systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 37*(1), 32-64.

Endsley, M. R., & Kiris, E. O. (1995). The out-of-the-loop performance problem and level of control in automation. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 37*(2), 381-394.

Federal Aviation Administration. (2012). *Integration of Unmanned Aircraft Systems into the National Airspace System: Concept of Operations*. Federal Aviation Administration Retrieved from https://www.suasnews.com/wp-content/uploads/2012/10/FAA-UAS-Conops-Version-2-0-1.pdf.

Federal Aviation Administration. (2013). *Integration of Civil Unmanned Aircraft Systems (UAS) in the National Airspace System (NAS) Roadmap*. Retrieved from https://www.faa.gov/uas/media/uas_roadmap_2013.pdf

Federal Aviation Administration. (2014). *Aeronautical Information Manual*. Retrieved from https://www.faa.gov/air_traffic/publications/media/aim_basic_4-03-14.pdf

Fern, L., Kenny, C. A., Shively, R. J., & Johnson, W. (2012). *UAS integration into the NAS: An examination of baseline compliance in the current airspace system*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Fern, L., Rorie, R. C., Pack, J. S., Shively, R. J., & Draper, M. H. (2015). *An evaluation of detect and avoid (DAA) displays for unmanned aircraft systems: The effect of information level and display location on pilot performance*. Paper presented at the 15th AIAA Aviation Technology, Integration, and Operations Conference.

Fern, L., & Shively, J. (2011). *Designing airspace displays to support rapid immersion for UAS handoffs*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Fitts, P. M. (1954). The information capacity of the human motor system in controlling the amplitude of movement. *Journal of experimental psychology, 47*(6), 381.

Friedman-Berg, F., Rein, J., & Racine, N. (2014). *Minimum visual information requirements for detect and avoid in unmanned aircraft systems.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Green, D. M., & Swets, J. A. (1989). *Signal Detection Theory and Psychophysics*. New York: John Wiley and Sons.

Hardman, N., Colombi, J., Jacques, D., Hill, R. R., & Miller, J. E. (2009). An evaluation of collision avoidance technologies using empirical function allocation. *Int J Appl Aviat Stud, 9*, 133-154.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. *Advances in psychology, 52*, 139-183.

Hobbs, A., & Lyall, B. (2015). *Human factors guidelines for unmanned aircraft system ground control stations*. Retrieved from http://humanfactors.arc.nasa.gov/publications/GCS_HF%20_Prelim_Guidelines_Hobbs_Lyall.pdf

Holmqvist, K., Nystrom, M., Andersson, R., Dewhurst, R., Jarodzka, H., & van de Weijer, J. (2011). *Eye tracking: A comprehensive guide to methods and measures*. New York: Oxford University Press.

Hunter, D. R. (2002). *Risk perception and risk tolerance in aircraft pilots*. Retrieved from

Hunter, D. R. (2005). Measurement of hazardous attitudes among pilots. *The International Journal of Aviation Psychology, 15*(1), 23-43.

Hunter, D. R., & Burke, E. F. (2002). Predicting aircraft pilot-training success: A meta-analysis of published research. *The International Journal of Aviation Psychology, 4*(4), 297-313.

Hursch, C. J., Hammond, K. R., & Hursch, J. L. (1964). Some methodological considerations in multiple-cue probability. *Psychological Review, 71*, 42-60.

Jenkins, D. P. (2012). Using cognitive work analysis to describe the role of UAVs in military operations. *Theoretical Issues In Ergonomics Science, 13*(3), 335-357. doi:10.1080/1463922X.2010.506560

Joint Planning and Development Office. (2012). Research, Development and Demonstration Roadmap: Version.

Kennedy, Q., Taylor, J. L., Reade, G., & Yesavage, J. A. (2010). Age and expertise effects in aviation decision making and flight control in a flight simulator. *Aviation, space, and environmental medicine, 81*(5), 489-497.

Kenny, C., & Fern, L. (2012). Varying levels of automation on UAS operator responses to traffic resolution advisories in civil airspace. *Advances in human aspects of aviation*, 279-288.

Kenny, C., Shively, R. J., & Jordan, K. (2014). *Unmanned aircraft system (UAS) delegation of separation in NextGen airspace*. Retrieved from http://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20140017682.pdf

Kirlik, A. (1993). Modeling strategic behavior in human-automation interaction: Why an" aid" can (and should) go unused. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 35*(2), 221-242.

Klein, G. (2008). Naturalistic decision making. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 50*(3), 456-460.

Lam, T. M., Mulder, M., & van Paassen, M. M. (2007). Haptic interface for UAV collision avoidance. *The International Journal of Aviation Psychology, 17*(2), 167-195.

Lee, D. W., & Bass, E. J. (2015). *Simulating Task Sharing with Delegation for Autonomy and Authority in Air Traffic Control.* Paper presented at the Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on.

Lee, J.-W., & Yates, J. F. (1992). How quantity judgment changes as the number of cues increases: An analytical framework and review. *Psychological Bulletin, 112*(2), 363.

Lee, S. M., & Mueller, E. R. (2013). *A systems-based approach to functional decomposition and allocation for developing UAS separation assurance concepts.* Paper presented at the 2013 Aviation Technology, Integration, and Operations Conference, August 12, 2013 - August 14, 2013, Los Angeles, CA, United states.

McCarley, J. S., & Wickens, C. D. (2005). *Human factors implications of UAVs in the national airspace*: University of Illinois at Urbana-Champaign, Aviation Human Factors Division.

Miller, C. A., & Parasuraman, R. (2007). Designing for flexible interaction between humans and automation: Delegation interfaces for supervisory control. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 49*(1), 57-75.

Monk, K., Shively, R. J., Fern, L., & Rorie, R. C. (2015). *Effects of display location and information level on UAS pilot assessments of a detect and avoid system*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Murphy, A. H. (1988). Skill scores based on the mean square error and their relationships to the correlation coefficient. *Monthly weather review, 116*(12), 2417-2424.

Nehme, C. E., Crandall, J. W., & Cummings, M. (2007). *An operator function taxonomy for unmanned aerial vehicle missions.* Paper presented at the 12th international command and control research and technology symposium.

Nielsen, J. (1993). *Usability engineering*. San Diego, CA: Academic Press.

Nullmeyer, R. T., Montijo, G. A., Herz, R., & Leonik, R. (2007). *Birds of prey: Training solutions to human factors issues*. Retrieved from

Onnasch, L. (2015). Crossing the boundaries of automation—Function allocation and reliability. *International Journal of Human-Computer Studies, 76*, 12-21.

Onnasch, L., Wickens, C. D., Li, H., & Manzey, D. (2014). Human Performance Consequences of Stages and Levels of Automation An Integrated Meta-Analysis. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 0018720813501549.

Pack, J. S., Draper, M. H., Darrah, S. J., Squire, M. P., & Cooks, A. (2015). *Exploring performance differences between UAS sense-and-avoid displays*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 39*(2), 230-253.

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 30*(3), 286-297.

Pauley, K., O'Hare, D., & Wiggins, M. (2008). Risk tolerance and pilot involvement in hazardous events and flight into adverse weather. *Journal of safety research, 39*(4), 403-411.

Potter, S. S., & Bressler, J. R. (1989). *Subjective Workload Assessment Technique (SWAT): A User's Guide*. Retrieved from

Prinet, J. C., Terhune, A., & Sarter, N. B. (2012). *Supporting dynamic re-planning in multiple UAV control: A comparison of 3 levels of automation*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Pritchett, A. R. (2001). Reviewing the role of cockpit alerting systems. *Human Factors and Aerospace Safety, 1*(1).

Pritchett, A. R., Kim, S. Y., & Feigh, K. M. (2014). Measuring human-automation function allocation. *Journal of Cognitive Engineering and Decision Making, 8*(1), 52-77.

Rash, C. E., LeDuc, P. A., & Manning, S. D. (2006). Human factors in US military unmanned aerial vehicle accidents *Human Factors of Remotely Operated Vehicles* (Vol. 7, pp. 117-131).

Rorie, R. C., & Fern, L. (2014). *UAS measured response: The effect of GCS control mode interfaces on pilot ability to comply with ATC clearances*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Rorie, R. C., & Fern, L. (2015). *The impact of integrated maneuver guidance information on UAS pilots performing the detect and avoid task*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Rorie, R. C., Fern, L., & Shively, J. (2016). *The impact of suggestive maneuver guidance on UAS pilot performing the detect and avoid function*. Paper presented at the AIAA Infotech@ Aerospace.

RTCA Inc. (2010). *Operational services and environmental definition (OSED) for unmanned aircraft systems (uas)*. Retrieved from http://www.rtca.org

Rudnick, G., Clauß, S., & Schulte, A. (2014). *Flight testing of agent supervisory control on heterogeneous unmanned aerial system platforms.* Paper presented at the 2014 IEEE/AIAA 33rd Digital Avionics Systems Conference (DASC), 5-9 Oct. 2014, Piscataway, NJ, USA.

Ruff, H. A., Draper, M. H., Lu, L. G., Poole, M. R., & Repperger, D. W. (2000). *Haptic feedback as a supplemental method of alerting UAV operators to the onset of turbulence*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Ruff, H. A., Narayanan, S., & Draper, M. H. (2002). Human interaction with levels of automation and decision-aid fidelity in the supervisory control of multiple simulated unmanned air vehicles. *Presence: Teleoperators and virtual environments, 11*(4), 335-351.

Salomon, K. A., Ferraro, F. R., Petros, T., Bernhardt, K., & Rhyner, K. (2015). *Individual differences in multitasking performance.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Santiago, C., & Mueller, E. R. (2015). *Pilot Evaluation of a UAS Detect-and-Avoid System's Effectiveness in Remaining Well Clear.* Paper presented at the Eleventh UAS/Europe Air Traffic Management Research and Development Seminar (ATM2015).

Scheff, S. (2014). *Ground control station catalog*. Retrieved from https://hfdesignworks.com/gcs

Schmidt, F. L., & Hunter, J. E. (1998). The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings. *Psychological Bulletin, 124*(2), 262.

Schreiber, B. T., Lyon, D. R., Martin, E. L., & Confer, H. A. (2002). *Impact of prior flight experience on learning Predator UAV operator skills. Mesa, AZ: Air Force Research Laboratory; 2002 Feb. Report No*. Retrieved from http://www.dtic.mil/dtic/tr/fulltext/u2/a401588.pdf

Seagull, F. J., & Sanderson, P. M. (2001). Anesthesia alarms in context: An observational study. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 43*(1), 66-78.

Sheridan, T. B., & Verplank, W. L. (1978). *Human and computer control of undersea teleoperators*. Retrieved from

Shively, R. J., Neiswander, G. M., & Fern, L. (2011). *Manned-unmanned teaming: Delegation control of Unmanned Aerial Systems (UAS).* Paper presented at the 67th American Helicopter Society International Annual Forum 2011, May 3, 2011 - May 5, 2011, Virginia Beach, VA, United states.

Stanard, T., Bearden, G., & Rothwell, C. (2013). *A cognitive task analysis to elicit preliminary requirements for an automated UAV verification planning system*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Stewart, T. R. (1990). A decomposition of the correlation coefficient and its use in analyzing forecasting skill. *Weather and forecasting, 5*(4), 661-666.

Stewart, T. R., & Lusk, C. M. (1994). Seven components of judgmental forecasting skill: Implications for research and the improvement of forecasts. *Journal of Forecasting, 13*(7), 579-599.

Tang, Z., & Zhang, A. (2013). *Human-machine-cooperation design methodology for civil aircraft cockpit.* Paper presented at the 2nd International Symposium on Computer, Communication, Control and Automation.

Theunissen, E., Tadema, J., & Goossens, A. (2009). *Exploring network enabled concepts for U (C) AV payload driven navigation.* Paper presented at the Digital Avionics Systems Conference, 2009. DASC'09. IEEE/AIAA 28th.

Tucker, L. R. (1964). A suggested alternative formulation in the developments by Hursch, Hammond, and Hursch, and by Hammond, Hursch, and Todd. *Psychological Review, 71*(6), 528.

Tvaryanas, A. P. (2006). *Human factors considerations in migration of unmanned aircraft system (UAS) operator control*. Retrieved from http://www.wpafb.af.mil/shared/media/document/AFD-090121-046.pdf

Van Dijk, H., & De Reus, A. (2010). *Automation and multiple ua control.* Paper presented at the 27th Congress of the International Council of the Aeronautical Sciences 2010, ICAS 2010, September 19, 2010 - September 24, 2010, Nice, France.

Wickens, C. D., & Dixon, S. (2002). *Workload demands of remotely piloted vehicle supervision and control: (1) single vehicle performance*. Retrieved from http://www.dtic.mil/dtic/tr/fulltext/u2/a496813.pdf

Wickens, C. D., Dixon, S., & Chang, D. (2003). *Using interference models to predict performance in a multiple-task UAV environment-2 UAVs*. Retrieved from http://www.aviation.illinois.edu/avimain/papers/research/pub_pdfs/techreports/03-09.pdf

Wickens, C. D., Dixon, S. R., & Johnson, N. (2006). *Imperfect diagnostic automation: An experimental examination of priorities and threshold setting*. Paper presented at the Human Factors and Ergonomics Society Annual Meeting.

Wickens, C. D., Lee, J. D., Liu, Y., & Gordon Becker, S. E. (2003). *An Introduction to Human Factors Engineering*: Prentice-Hall, Inc.

Wickens, C. D., Li, H., Santamaria, A., Sebok, A., & Sarter, N. B. (2010). *Stages and levels of automation: An integrated meta-analysis.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Williams, K. W. (2004). *A summary of unmanned aircraft accident/incident data: Human factors implications*. Retrieved from http://www.dtic.mil/get-tr-doc/pdf?AD=ADA460102

Williams, K. W. (2006). *Human factors implications of unmanned aircraft accidents: Flight-control problems*. Retrieved from https://ntl.bts.gov/lib/34000/34000/34063/GetTRDoc.pdf

Williams, K. W. (2007). *An assessment of pilot control interfaces for unmanned aircraft*. Retrieved from http://www.faa.gov/data_research/research/med_humanfacs/oamtechreports/2000s/media/200708.pdf

Williams, K. W. (2008). *Documentation of sensory information in the operation of unmanned aircraft systems*. Retrieved from http://www.faa.gov/data_research/research/med_humanfacs/oamtechreports/2000s/media/200823.pdf

Williams, K. W. (2012). *An investigation of sensory information, levels of automation, and piloting experience on unmanned aircraft pilot performance*. Retrieved from http://www.faa.gov/data_research/research/med_humanfacs/oamtechreports/2010s/media/201204.pdf

6. APPENDIX A1: SQL QUERIES USED FOR RESEARCH GAP ANALYSIS

1. Function Allocation Strategy

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Information Acquisition'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Single Information Source'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Single Information Source' AND FA_Lvl3 = 'None'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Single Information Source' AND FA_Lvl3 = 'Assisted'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Single Information Source' AND FA_Lvl3 = 'Processed Data Presentation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Single Information Source' AND FA_Lvl3 = 'Mixed Initiative Data Presentation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Multiple Information Sources'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Multiple Information Sources' AND FA_Lvl3 = 'None'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Multiple Information Sources' AND FA_Lvl3 = 'Assisted'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Multiple Information Sources' AND FA_Lvl3 = 'Processed Data Presentation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Multiple Information Sources' AND FA_Lvl3 = 'Mixed Initiative Data Presentation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Information Analysis'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Information Analysis' AND FA_Lvl2 = 'None'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Mixed Initiative Reference Generation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Automated Reference Generation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Automated Situation Assessment'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Automated Situation Assessment and Reference Generation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Automated Situation Assessment and Reference Generation with Alerting'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Automated Situation Assessment and Mixed Initiative Reference Generation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Automated Situation Assessment and Mixed Initiative Reference Generation with Alerting'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Mixed Initiative Situation Assessment'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Mixed Initiative Situation Assessment and Automated Reference Generation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Mixed Initiative Situation Assessment and Automated Reference Generation with Alerting'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Mixed Initiative Situation Assessment and Reference Generation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl2 = 'Mixed Initiative Situation Assessment and Reference Generation with Alerting'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Decision and Action Selection'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Decision and Action Selection' AND FA_Lvl2 = 'None'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Decision and Action Selection' AND FA_Lvl2 = 'Assisted Option Generation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Decision and Action Selection' AND FA_Lvl2 = 'Automated Option Generation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Decision and Action Selection' AND FA_Lvl2 = 'Filtered Option Generation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Decision and Action Selection' AND FA_Lvl2 = 'Automated Option Ordering'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Decision and Action Selection' AND FA_Lvl2 = 'Mixed Initiative Option Generation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Decision and Action Selection' AND FA_Lvl2 = 'Management by Consent'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Decision and Action Selection' AND FA_Lvl2 = 'Management by Exception'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Decision and Action Selection' AND FA_Lvl2 = 'Mixed Initiative Decision Selection'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Decision and Action Selection' AND FA_Lvl2 = 'Fully Automated Decision Selection'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Action Implementation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Action Implementation' AND FA_Lvl2 = 'None'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Action Implementation' AND FA_Lvl2 = 'Compulsory Feedback'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Action Implementation' AND FA_Lvl2 = 'Feedback by Request'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Action Implementation' AND FA_Lvl2 = 'Feedback by Design'

SELECT COUNT(Title) FROM papers_output_tbl WHERE FA_Lvl1 = 'Action Implementation' AND FA_Lvl2 = 'No Feedback'

2. Measures

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl1 = 'Function Allocation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'System Workload/Taskload'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Mismatches Between Responsibility and Authority'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Work Environment Stability'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Function Allocation Coherence'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Interruptions'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Automation Boundary Conditions'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Adaptation to Context'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl1 = 'Human-Automation Interaction'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Trust'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Situation Awareness'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Mental Workload'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Adaptation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Reliance'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Utilization'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl1 = 'Mission Performance'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Fuel Consumption'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Conflict Resolution Maneuver Quality'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Delay'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Compiance'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Flight Path Error'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Lateral'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Vertical'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Speed Error'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl1 = 'Detection and Assessment'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Signal Detection'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Sensitivity'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl4 = 'Hit Rate'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl4 = 'Miss Rate'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl4 = 'Correct Rejection Rate'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl4 = 'False Alarm Rate'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Response Bias'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Lens Model'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Accuracy'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Consistency'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Judgment Strategy'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Skill Score'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Skill Score'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Conditional Bias'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Unconditional Bias'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl1 = 'Control'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Response Time'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Alert'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Air Traffic Control'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Target'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Target'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Airspace Configuration'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl3 = 'Abnormal System Status'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Fitts Law'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl1 = 'Attention Allocation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Fixation Frequency'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Glance Duration'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Fixation Duration'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl2 = 'Total Viewing Time'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Measures_Lvl1 = 'Subjective Usability'

3. Task

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Phase of Flight'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Phase of Flight' AND Task_Lvl2 = 'Flight Planning'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Phase of Flight' AND Task_Lvl2 = 'Engine Start'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Phase of Flight' AND Task_Lvl2 = 'Taxi'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Phase of Flight' AND Task_Lvl2 = 'Takeoff'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Phase of Flight' AND Task_Lvl2 = 'Departure'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Phase of Flight' AND Task_Lvl2 = 'En Route'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Phase of Flight' AND Task_Lvl2 = 'Aerial Work/Mission'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Phase of Flight' AND Task_Lvl2 = 'Descent'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Phase of Flight' AND Task_Lvl2 = 'Approach'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Phase of Flight' AND Task_Lvl2 = 'Landing'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Generic Functions'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Manage'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Plan for Normal Conditions'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Plan for Non-normal Conditions'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Make Decisions in Normal Conditions'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Recognize and Respond to Non-normal Conditions'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Transfer Control'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Aviate'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Monitor and Control Aircraft Systems (incl. Automation)'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Monitor Consumable Resources'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Monitor and Configure Control Station'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Maneuver Aircraft to Avoid Collision'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Monitor and Control Status of Control Links'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Navigate'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Control and Monitor Aircraft Location and Flight Path'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Remain Clear of Terrain, Airspace Boundaries, and Weather'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Self-separate from Other Aircraft'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Ensure Lost Link Procedure Remains Appropriate'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Terminate Flight'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Communicate'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Air Traffic Control'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl4 = 'Ground Control'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl4 = 'Local Control'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl4 = 'Terminal Radar Approach Control'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl4 = 'Air Route Traffic Control Center'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Pilots of other Aircraft'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Crew Members'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Ancillary Services'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Mission'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military' AND Task_Lvl3 = 'Reconnaissance/Surveillance'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military' AND Task_Lvl3 = 'Tactical Strike'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military' AND Task_Lvl3 = 'Communication Relay'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military' AND Task_Lvl3 = 'Signal Intelligence'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military' AND Task_Lvl3 = 'Maritime Patrol'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military' AND Task_Lvl3 = 'Penetrating Strike'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military' AND Task_Lvl3 = 'Suppression of Enemy Air Defenses (SEAD)'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military' AND Task_Lvl3 = 'Aerial Refueling'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military' AND Task_Lvl3 = 'Counter Air'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military' AND Task_Lvl3 = 'Airlift'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military' AND Task_Lvl3 = 'Target Search'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Military' AND Task_Lvl3 = 'Target Identification'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Atmospheric Research'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Border Patrol'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Disaster Response'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Hurricane Measurement and Tracking'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Forest Fire Monitoring and Support'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Search and Rescue'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Maritime Surveillance'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Law Enforcement'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Humanitarian Aid'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Aerial Imaging and Mapping'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Drug Surveillance and Interdiction'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Monitor and Inspect Critical Infrastructure'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Natural Hazard Monitoring'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Airborne Pollution Observation and Tracking'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Chemicals and Petroleum Spill Monitoring'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Communications Relay'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Traffic Monitoring'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Civil' AND Task_Lvl3 = 'Port Security'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Comercial'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Crop Monitoring'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Fish Spotting'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Remote Imaging and Mapping'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Utility Inspections'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Mining Exploration'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Agricultural Applications'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Communication Relay'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Petroleum Spill Monitoring'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Site Security'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Broadcast Services'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'News Media Support'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Filming'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Real Estate Photos'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Aerial Advertising'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Commercial' AND Task_Lvl3 = 'Cargo'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl1 = 'Flight Event'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Nominal'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl2 = 'Failure'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Vehicle Equipment'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Control Station Equipment'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'Control Link'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Task_Lvl3 = 'ATC Communication'

4. Environment

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl1 = 'Atmospheric'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Wind'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Visibility'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Weather'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Sky Conditions'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Air Temperature'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Pressure'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Precipitation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Turbulence'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Ice'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl1 = 'Lighting'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Day'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Night'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl1 = 'Intruder Traffic'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Vehicle Type'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = 'Airship'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = 'Glider'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = 'Helicopter'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = 'Manned Powered Aircraft'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = 'Unmanned Powered Aircraft'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Position Broadcast Equipment'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = 'Radar-Based'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = 'Satellite-Based'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = 'ADS-B'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = 'Mixed'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Position Broadcast Equipment' AND Environment_Lvl3 = 'None'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Density'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Density' AND Environment_Lvl3 = 'None'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = 'Unspecified'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = '< 5 Intruder Encounters'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = '5 to 10 Intruder Encounters'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl3 = '> 10 Intruder Encounters'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl1 = 'Geography'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Restricted Airspace'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Building'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Natural Obstacle'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'No Obstacles'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Environment_Lvl2 = 'Other Obstacle'

5. National Airspace Context

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl1 = 'Airspace'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl2 = 'Class A'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl2 = 'Class B'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl2 = 'Class C'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl2 = 'Class D'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl2 = 'Class E Below A'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl2 = 'Class E Above A'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl2 = 'Class G'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl1 = 'Oceanic'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl1 = 'Surface'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl2 = 'Airport'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl2 = 'Non-airport Ground'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl2 = 'Watercraft'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl1 = 'Flight Rules'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl2 = 'VFR'

SELECT COUNT(Title) FROM papers_output_tbl WHERE National_Airspace_Lvl2 = 'IFR'

6. Participants/Crew

SELECT COUNT(Title) FROM papers_output_tbl WHERE Crew_Lvl1 = 'Pilot-in-command'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Crew_Lvl2 = 'Manned Aircraft Experience'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Crew_Lvl2 = 'Unmanned Aircraft Experience'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Crew_Lvl2 = 'Mixed Experience'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Crew_Lvl2 = 'No Prior Flying Experience'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Crew_Lvl2 = 'Unspecified'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Crew_Lvl1 = 'External Pilot'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Crew_Lvl1 = 'Payload Operator'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Crew_Lvl1 = 'Visual Observer'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Crew_Lvl2 = 'Ground'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Crew_Lvl2 = 'Airborne'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Crew_Lvl1 = 'Mission Commander'

7. Control Station

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl1 = 'Hardware'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Suite'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Desktop'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Laptop'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl1 = 'Control Devices'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Stick-and-throttle'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Joystick'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Point-and-click'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Knobs'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Touch Screen'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Keyboard'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl1 = 'Information Display'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Out-window'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Moving map'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'System status'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Traffic information'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Weather information'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Payload status'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Communication client'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Vertical Situation Display'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Navigation Display'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Electronic Checklist'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ctrl_Station_Lvl2 = 'Horizontal Situation Indicator'

8. Ownship

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'RQ-4 Global Hawk'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'X-47B N-UCAS'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Gulfstream 550'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MQ-9 Predator B/Reaper'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'King Air 200'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Cessna Caravan'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'RQ-5 Hunter'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'RQ-2 Pioneer'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MQ-1 Predator A'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'RQ-7 Shadow'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Cessna 182'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aerosonde Mk47'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'ScanEagle'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Cessna 172'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'RQ-8A FireScout'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Bell 206'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Hummingbird A-160'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'RMAX TYPE II'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Honeywell RQ-16A T-Hawk'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Generic Helicopter'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Generic Multirotor'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'SA 60 LAA'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'WLD 1B'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Global Observer HALE'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Raven'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Generic MALE'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Unspecified'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'RQ-6 Outrider'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aurora Flight Sciences Goldeneye-80'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aurora Flight Sciences Perseus'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Bell Helicopter Textron Eagle'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'General Atomics Altair'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'AeroVironment Raven B'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'AeroVironment Helios'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'AeroVironment Pathfinder'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'AeroVironment Puma'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aerosystems ZALA 421'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'AAI Aerosonde Mark 4.7'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MQ-1C ER/MP Sky Warrior/Gray Eagle'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'A160 Hummingbird'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Northrup Grumman LEMV Airship'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Northrup Grumman BAT-12'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aurora Flight Sciences Orion'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aurora Flight Sciences Centaur'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'ADCOM YABHON'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'ATE Vulture'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aero Design and Development Hornet'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aeronautics Defense Systems Aerostar'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aeronautics Defense Systems Aerolight'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aeronautics Defense Systems Aerosky'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aeroscout Scout B1-100'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Explorer Tandem Wing'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aurora Flight Sciences Excalibur'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'BAE Systems Phoenix'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'ACR Silver Fox'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'BAE Systems Skylynx'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Baykar Makina'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Warrior Gull'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'GNAT 750'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'DarkStar'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'BAE Systems Kingfisher'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'BAE Systems Silverfox'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'EMIT Sparrow'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MBDA Fire Shadow'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'EADS Dornier'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Meggitt Barracuda'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Meggitt Hammerhead'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Meggitt Vindicator'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MLB Super Bat'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Arcturus T-20'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Dara Aviation D-1'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Denel Dynamics Seeker'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Denel Dynamics Bateleur'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'DRS Neptune RQ-15'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Elbit Systems Hermes'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'EMT LUNA X-2000'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'ENICS E08 Aerial Decoy'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'ENICS BERTA'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Fuji RPH-2A'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Innocon minFalcon'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Innocon MicroFalcon'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Boeing Integrator'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Boeing Insight'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Integrated Dynamics Explorer'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Integrated Dynamics Border Eagle'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Integrated Dynamics Vision MK'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Integrated Dynamics Hawk'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Integrated Dynamics Vector'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'International Aviation Supply Raffaello'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Ranger'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Heron'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'IAI NRUAV'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Husky Autonomous Helicopter'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'L-3 Viking'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'L-3 TigerShark'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MSI BQM'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MSI Chukar'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MSI Firejet'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MSI MQM'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MSI QUH-1 Rotary Wing'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MSI QST-35'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MSI Falconet'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'MSI High Speed Maneuvarable Surface Target'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Raytheon KillerBee'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Raytheon Cobra'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'ACR Manta'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Rheinmetall KZO'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Rheinmetall OPALE'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Rheinmetall Mucked'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Rheinmetall Tares/Taifun'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Rheinmetall Fledermaus'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Rodian/Automasjonsutvikling AS Xr-T9'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Rodian/Automasjonsutvikling AS Xr-T8'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Sagum Crecerelle'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Sagum Sperwer'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Sagum Patroller'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'SAIC Vigilante'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Satuma Jasoos'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Satuma Mukhbar'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Satuma Flamingo'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Schiebel Camcopter'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'SA-200 Weasel'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Selex Galileo Mirach'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Selex Galileo Falco'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Skycam Hawk'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Snap Defense Systems Stingray'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Snap Defense Systems Bandit'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Snap Defense Systems Scout'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Snap Defense Systems Aggressor'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Snap Defense Systems Sea Vixen'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Snap Defense Systems Blacklash'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Snap Defense Systems Centurion'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Thales Watchkeeper WK450'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'TAI ANKA'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Cyber Tech CyberEye'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Cyber Tech CyberQuad'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Cyber Tech CyBird'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Cyber Tech CyberWraith'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'UCon System RemoEye'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Unmanned Systems Group ATRO-X'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Unmanned Systems Group CT-450 Discover 1'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'UVision Blue Horizon'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'UVision Blade Arrow'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'UVision MALE UAS'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'UVision Sparrow'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Aeroscout B1-100'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Ownship_Lvl2 = 'Xian ASN'

9. Type of Study

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl1 = 'Accident Data Analysis'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl1 = 'Computational Modeling'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Agent Based Simulation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Discrete Event Simulation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Markov Decision Process'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl1 = 'Field Test'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl1 = 'Human Factors Design and Evaluation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Task Analysis'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Observation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Participant Questionnaire'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Heuristic Evaluation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Think-Aloud Verbal Protocol'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Subject Matter Expert Interview'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Focus Group'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl1 = 'Human-in-the-loop Simulation'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl1 = 'Literature Review/Meta-analysis'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'General Human-Automation Interaction'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'UAV-Specific'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl1 = 'Products of the Systems Engineering Lifecycle'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Operational Concept/Integration Plan'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Requirements/Design Recommendations'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Design'

SELECT COUNT(Title) FROM papers_output_tbl WHERE Approach_Lvl2 = 'Prototype'

7. APPENDIX A2: FULL LIST OF ARTICLES REVIEWED

Abbott, K. H. (2001). Human Factors Engineering and Flight Deck Design. The Avionics Handbook, 9-1-9-15.

Adams, J. A. (2015). Cognitive Task Analysis for Unmanned Aerial System Design Handbook of Unmanned Aerial Vehicles (pp. 2425-2441): Springer.

Adams, J. A., Humphrey, C. M., Goodrich, M. A., Cooper, J. L., Morse, B. S., Engh, C., & Rasmussen, N. (2009). Cognitive Task Analysis for Developing Unmanned Aerial Vehicle Wilderness Search Support. Journal of Cognitive Engineering and Decision Making, 3(1), 1-26. doi:10.1518/155534309x431926

Arrabito, G. R., Ho, G., Lambert, A., Rutley, M., Keillor, J., Chiu, A., . . . Hou, M. (2010). Human Factors Issues for Controlling Uninhabited Aerial Vehicles.

Astrov, I., & Pedai, A. (2008). Enhancing situational awareness by means of hybrid adaptive neural control of vertical flight in unmanned helicopter. Paper presented at the 2008 International Conference on Control, Automation and Systems, ICCAS 2008, October 14, 2008 - October 17, 2008, Seoul, Korea, Republic of.

Bainbridge, L. (1983). Ironies of automation. Automatica, 19(6), 775-779.

Barnes, M. J., Knapp, B. G., Tillman, B. W., Walters, B. A., & Velicki, D. (2000). Crew systems analysis of unmanned aerial vehicle (UAV) future job and tasking environments. Retrieved from http://www.dtic.mil/dtic/tr/fulltext/u2/a374230.pdf

Bass, E. J., & Pritchett, A. R. (2008). Human-automated judge learning: A methodology for examining human interaction with information analysis automation. Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 38(4), 759-776.

Beainy, F., Anh, M., & Commuri, S. (2009). Unmanned aerial vehicles operational requirements and fault-tolerant robust control in level flight. Paper presented at the 2009 17th Mediterranean Conference on Control and Automation (MED), 24-26 June 2009, Piscataway, NJ, USA.

Bell, B., Feiner, S., & Höllerer, T. (2001). View management for virtual and augmented reality. Paper presented at the Proceedings of the 14th annual ACM symposium on User interface software and technology.

Berson, B., Gershzohn, G., Boltz, L., Wolf, R., & Schultz, M. (2005). Human Systems Integration: Requirements and Functional Decomposition.

Billings, C. E. (1996). Human-centered aviation automation: Principles and guidelines.

Billings, D. R., & Durlach, P. J. (2008). The Effects of Input Device and Latency on Ability to Effectively Pilot a Simulated Micro-UAV. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Bindewald, J. M. (2015). Adaptive Automation Design and Implementation. DTIC Document. Retrieved from http://www.dtic.mil/cgi-bin/GetTRDoc?Location=U2&doc=GetTRDoc.pdf&AD=ADA623873 Defense Technical Information Center database.

Bocaniala, C. D., & Sastry, V. V. S. S. (2010). On Enhanced Situational Awareness Models for Unmanned Aerial Systems. Paper presented at the 2010 IEEE Aerospace Conference, 6-13 March 2010, Piscataway, NJ, USA.

Boussemart, Y., Las Fargeas, J., Cummings, M. L., & Roy, N. (2009). Comparing learning techniques for hidden Markov Models of human supervisory control behavior. Paper presented at the AIAA Infotech@ Aerospace'09 Conference, Seattle, Washington.

Boy, G. A. (2014). Requirements for Single Pilot Operations in Commercial Aviation: A First High-Level Cognitive Function Analysis. Paper presented at the CSDM (Posters).

Buondonno, K., & Dressel, J. (2011). RQ-7B Shadow UAS Operational Assessment: Marine Corps Air Station, Cherry Point, NC. Retrieved from http://www.tc.faa.gov/its/worldpac/techrpt/tctn11-3.pdf

Calhoun, G., & Draper, M. (2012). Unmanned Aerial Vehicles: Enhancing Video Display Utility with Synthetic Vision Technology. Human-Robot Interactions in Future Military Operations.

Calhoun, G., Draper, M., Miller, C., Ruff, H., Breeden, C., & Hamell, J. (2013). Adaptable automation interface for multi-unmanned aerial systems control:Preliminary usability evaluation. Paper presented at the 57th Human Factors and Ergonomics Society Annual Meeting - 2013, HFES 2013, September 30, 2013 - October 4, 2013, San Diego, CA.

Calhoun, G., Draper, M. H., Ruff, H., Barry, T., Miller, C. A., & Hamell, J. (2012). Future Unmanned aerial systems control: Feedback on a highly flexible operator-automation delegation interface concept. Paper presented at the AIAA Infotech at Aerospace Conference and Exhibit 2012, June 19, 2012 - June 21, 2012, Garden Grove, CA.

Calhoun, G., Ruff, H., Draper, M., Wright, N., & Mullins, B. (2009). Levels of automation in multi-UAV control allocation and router tasks. Paper presented at the AIAA Infotech@ Aerospace Conference, Seattle, Washington, April.

Calhoun, G. L., & Draper, M. H. (2015). Display and Control Concepts for Multi-UAV Applications Handbook of Unmanned Aerial Vehicles (pp. 2443-2473): Springer.

Calhoun, G. L., Draper, M. H., Abernathy, M. F., Patzek, M., & Delgado, F. (2005). Synthetic vision system for improving unmanned aerial vehicle operator situation awareness. Paper presented at the Defense and Security.

Calhoun, G. L., Draper, M. H., & Ruff, H. A. (2009). Effect of level of automation on unmanned aerial vehicle routing task. Paper presented at the 53rd Human Factors and Ergonomics Society Annual Meeting 2009, HFES 2009, October 19, 2009 - October 23, 2009, San Antonio, TX.

Calhoun, G. L., Miller, C. A., Hughes, T. C., & Draper, M. H. (2014). UAS sense and avoid system interface design and evaluation. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Calhoun, G. L., Ward, V. B., & Ruff, H. A. (2011). Performance-based adaptive automation for supervisory control. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Chappell, S., & Dunlap, K. (2006). Incorporating operator situation awareness into the design process: A key ingredient for future combat unmanned rotorcraft. Paper presented at the ANNUAL FORUM PROCEEDINGS-AMERICAN HELICOPTER SOCIETY.

Chappell, S. L., & Valimont, R. B. (2013). North-up, Track-up, and Camera-up Navigation of Unmanned Aircraft Systems. Paper presented at the 17th International Symposium on Aviation Psychology, Dayton, OH.

Chen, J. Y., Barnes, M. J., & Harper-Sciarini, M. (2011). Supervisory control of multiple robots: Human-performance issues and user-interface design. Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, 41(4), 435-454.

Chen, T., Gonzalez, F., Campbell, D., & Coppin, G. (2014). Management of multiple heterogeneous UAVs using capability and autonomy visualisation: Theory, experiment and result. Paper presented at the 2014 International Conference on Unmanned Aircraft Systems, ICUAS 2014, May 27, 2014 - May 30, 2014, Orlando, FL.

Clapper, J., Young, J., Cartwright, J., & Grimes, J. (2007). Unmanned systems roadmap 2007-2032. Office of the Secretary of Defense, 188.

Clare, A. S., Ryan, J. C., Jackson, K. F., & Cummings, M. L. (2012). Innovative systems for Human Supervisory Control of Unmanned Vehicles. Paper presented at the Proceedings of the Human Factors and Ergonomics Society 56th Annual Meeting, HFES 2012, October 22, 2012 - October 26, 2012, Boston, MA.

Clauß, S., Bruggenwirth, S., Aurich, P., Schulte, A., Dobrokhodov, V., & Kaminer, I. (2012). Design and evaluation of a UAS combining cognitive automation and Optimal Control. Paper presented at the AIAA Infotech at Aerospace Conference and Exhibit 2012, June 19, 2012 - June 21, 2012, Garden Grove, CA.

Clauß, S., & Schulte, A. (2014). Implications for operator interactions in an agent supervisory control relationship. Paper presented at the 2014 International Conference on Unmanned Aircraft Systems, ICUAS 2014, May 27, 2014 - May 30, 2014, Orlando, FL.

Clothier, R. A., Palmer, J. L., Walker, R. A., & Fulton, N. L. (2011). Definition of an airworthiness certification framework for civil unmanned aircraft systems. Safety Science, 49(6), 871-885. doi:10.1016/j.ssci.2011.02.004

Clothier, R. A., & Wu, P. (2012). A review of system safety failure probability objectives for unmanned aircraft systems. Paper presented at the 11th International Probabilistic Safety

Assessment and Management Conference and the Annual European Safety and Reliability Conference 2012, PSAM11 ESREL 2012, June 25, 2012 - June 29, 2012, Helsinki, Finland.

Clough, B. T. (2003). Unmanned aerial vehicles: Autonomous control challenges, a researcher's perspective. Paper presented at the 2nd AIAA "Unmanned Unlimited" Conference and Workshop and Exhibit 2003, September 15, 2003 - September 18, 2003, San Diego, CA.

Colomina, I., & Molina, P. (2014). Unmanned aerial systems for photogrammetry and remote sensing: A review. ISPRS Journal of Photogrammetry and Remote Sensing, 92, 79-97. doi:10.1016/j.isprsjprs.2014.02.013

Comstock Jr, J. R., McAdaragh, R., Ghatas, R. W., Burdette, D. W., & Trujillo, A. C. (2014). UAS in the NAS: Survey responses by ATC, manned aircraft pilots, and UAS pilots.

Consiglio, M. C., Chamberlain, J. P., Munoz, C. A., & Hoffler, K. D. (2012). Concepts of Integration for UAS Operations in the NAS.

Cook, M. B., & Smallman, H. S. (2013). Human-centered command and control of future autonomous systems. Retrieved from http://www.dtic.mil/cgi-bin/GetTRDoc?Location=U2&doc=GetTRDoc.pdf&AD=ADA588335

Cook, M. B., Smallman, H. S., Lacson, F. C., & Manes, D. I. (2010). Situation displays for dynamic UAV replanning: Intuitions and performance for display formats. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Cook, M. B., Smallman, H. S., Lacson, F. C., & Manes, D. I. (2012). Guided Attention For Autonomous System Supervision. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Cooke, N. J., & Shope, S. M. (2004). Designing a synthetic task environment. Scaled worlds: Development, validation, and application, 263, 278.

Cosenzo, K., Parasuraman, R., & Pillalamarri, K. (2008). The effect of task based automation for the control of unmanned systems on operator performance. Paper presented at the 52nd Human Factors and Ergonomics Society Annual Meeting, HFES 2008, September 22, 2008 - September 26, 2008, New York, NY.

Crouse, J. D. (2007). Development of Cursor-On-Target Control for Semi-Autonomous Unmanned Aircraft Systems. DTIC Document. Retrieved from http://www.dtic.mil/dtic/tr/fulltext/u2/a469942.pdf Defense Technical Information Center database.

Cummings, M., Marquez, J., & Visser, M. (2007). Shadow TUAV Single Operator Consolidation: Display Assessment. Retrieved from http://hdl.handle.net/1721.1/46728

Cummings, M., & Mitchell, P. (2005). Managing multiple UAVs through a timeline display. Proceedings of the American Institute of Aeronautics and Astronautics Infotech@ Aerospace.

Cummings, M. L. (2004). The need for command and control instant message adaptive interfaces: Lessons learned from Tactical Tomahawk human-in-the-loop simulations. CyberPsychology & Behavior, 7(6), 653-661.

Cummings, M. L., Bertucelli, L. F., Macbeth, J., & Surana, A. (2014). Task versus vehicle-based control paradigms in multiple unmanned vehicle supervision by a single operator. IEEE Transactions on Human-Machine Systems, 44(3), 353-361. doi:10.1109/THMS.2014.2304962

Cummings, M. L., Bruni, S., Mercier, S., & Mitchell, P. (2007). Automation architecture for single operator, multiple UAV command and control. Retrieved from

Cummings, M. L., & Brzezinski, A. S. (2010). Global vs. local decision support for multiple independent UAV schedule management. International Journal of Applied Decision Sciences, 3(3), 188-205.

Cummings, M. L., Clare, A., & Hart, C. (2010). The role of human-automation consensus in multiple unmanned vehicle scheduling. Human Factors, 52(1), 17-27. doi:10.1177/0018720810368674

Cummings, M. L., & Guerlain, S. (2007). Developing operator capacity estimates for supervisory control of autonomous vehicles. Human Factors: The Journal of the Human Factors and Ergonomics Society, 49(1), 1-15.

Cummings, M. L., & Mitchell, P. J. (2007). Operator scheduling strategies in supervisory control of multiple UAVs. Aerospace Science and Technology, 11(4), 339-348. doi:10.1016/j.ast.2006.10.007

da Silva, F., Scott, S., & Cummings, M. (2007). Design Methodology for Unmanned Aerial Vehicle (UAV) Team Coordination. Humans and Automation Laboratory, Report# HAL2007-05.

Dalamagkidis, K., Valavanis, K. P., & Piegl, L. A. (2008). Current Status and Future Perspectives for Unmanned Aircraft System Operations in the US. Journal of Intelligent and Robotic Systems, 52(2), 313-329. doi:10.1007/s10846-008-9213-x

Dalamagkidis, K., Valavanis, K. P., & Piegl, L. A. (2008). On unmanned aircraft systems issues, challenges and operational restrictions preventing integration into the National Airspace System. Progress in Aerospace Sciences, 44(7-8), 503-519. doi:10.1016/j.paerosci.2008.08.001

Damilano, L., Guglieri, G., Quagliotti, F., Sale, I., & Lunghi, A. (2013). Ground Control Station Embedded Mission Planning for UAS. Journal of Intelligent & Robotic Systems, 69(1-4), 241-256. doi:10.1007/s10846-012-9697-2

Davis, K. D. (2008). Unmanned Aircraft Systems Operations in the US National Airspace System. Interim Operational Approval Guidance, 08-01.

De Visser, E., Shaw, T., Mohamed-Ameen, A., & Parasuraman, R. (2010). Modeling human-automation team performance in networked systems: Individual differences in working memory count. Paper presented at the 54th Human Factors and Ergonomics Society Annual Meeting 2010, HFES 2010, September 27, 2010 - October 1, 2010, San Francisco, CA.

De Visser, E. J., Jacobs, B., Chabuk, T., Freedy, A., & Scerri, P. (2012). Design and evaluation of the Adaptive Interface Management System (AIMS) for collaborative mission planning with unmanned vehicles. Paper presented at the AIAA Infotech at Aerospace Conference and Exhibit 2012, June 19, 2012 - June 21, 2012, Garden Grove, CA.

De Vries, M. F. L., Koeners, G. J. M., Roefs, F. D., Van Ginkel, H. T. A., & Theunissen, E. (2006). Operator support for time-critical situations: Design and evaluation. Paper presented at the 25th DASC Digital Avionics Systems Conference - Network-Center Environment: The Impact on Avionics and Systems, October 15, 2006 - October 19, 2006, Portland, OR.

Dearden, A., Harrison, M., & Wright, P. (2000). Allocation of function: scenarios, context and the economics of effort. International Journal of Human-Computer Studies, 52(2), 289-318.

DeBusk, W. M. (2010). Unmanned aerial vehicle systems for disaster relief: Tornado alley. Paper presented at the AIAA Infotech@ Aerospace Conference, AIAA-2010-3506, Atlanta, GA.

Delle Fave, F. M., Rogers, A., Xu, Z., Sukkarieh, S., & Jennings, N. R. (2012). Deploying the max-sum algorithm for decentralised coordination and task allocation of unmanned aerial vehicles for live aerial imagery collection. Paper presented at the 2012 IEEE International Conference on Robotics and Automation (ICRA), 14-18 May 2012, Piscataway, NJ, USA.

Department of Defense. (2008). Interface Standard Common Warfighting Symbology (Vol. MIL-STD-2525C).

Dionne, D., & Rabbath, C. A. (2007). Multi-UAV decentralized task allocation with intermittent communications: The DTC algorithm. Paper presented at the 2007 American Control Conference, ACC, July 9, 2007 - July 13, 2007, New York, NY.

Dixon, S. R., & Wickens, C. D. (2006). Automation reliability in unmanned aerial vehicle control: A reliance-compliance model of automation dependence in high workload. Human Factors: The Journal of the Human Factors and Ergonomics Society, 48(3), 474-486.

Dixon, S. R., Wickens, C. D., & Chang, D. (2005). Mission control of multiple unmanned aerial vehicles: A workload analysis. Human Factors: The Journal of the Human Factors and Ergonomics Society, 47(3), 479-487.

Donmez, B., Cummings, M. L., & Graham, H. D. (2009). Auditory decision aiding in supervisory control of multiple unmanned aerial vehicles. Human Factors: The Journal of the Human Factors and Ergonomics Society.

Draper, M. H., Miller, C. A., Benton, J., Calhoun, G. L., Ruff, H., Hamell, J., & Barry, T. (2013). Multi-Unmanned Aerial Vehicle Systems Control via Flexible Levels of Interaction: An Adaptable Operator-Automation Interface Concept Demonstration. Paper presented at the AIAA Infotech Aerospace Conference, 19-22 Aug. 2013, Reston, VA, USA.

Draper, M. H., Pack, J. S., Darrah, S. J., Moulton, S. N., & Calhoun, G. L. (2014). Human-Machine Interface development for common airborne sense and avoid program. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Dumas, P.-Y., Seghrouchni, A. E. F., & Taillibert, P. (2012). Aerial: A framework to support human decision making in a constrained environment. Paper presented at the 2012 IEEE 24th International Conference on Tools with Artificial Intelligence, ICTAI 2012, November 7, 2012 - November 9, 2012, Athens, Greece.

Durso, F. T., Stearman, E. J., Morrow, D. G., Mosier, K. L., Fischer, U., Pop, V. L., & Feigh, K. M. (2014). Exploring Relationships of Human-Automation Interaction Consequences on Pilots Uncovering Subsystems. Human Factors, 57(3), 397-406.

Eggers, J., & Draper, M. H. (2006). Multi-UAV control for tactical reconnaissance and close air support missions: operator perspectives and design challenges. Paper presented at the Proc. NATO RTO Human Factors and Medicine Symp. HFM-135. NATO TRO, Neuilly-sur-Siene, CEDEX, Biarritz, France.

Endsley, M. R., & Kaber, D. B. (1999). Level of automation effects on performance, situation awareness and workload in a dynamic control task. Ergonomics, 42(3), 462-492.

Endsley, M. R., & Kiris, E. O. (1995). The out-of-the-loop performance problem and level of control in automation. Human Factors: The Journal of the Human Factors and Ergonomics Society, 37(2), 381-394.

European Organization for the Safety of Air Navigation. (2009). Human Factors Case for the UAS-ATM Integration Part II: UAS VLOS Operation in Classes C and F/G Airspace. Retrieved from

Federal Aviation Administration. (2012). Integration of Unmanned Aircraft Systems into the National Airspace System: Concept of Operations. Federal Aviation Administration Retrieved from http://www.suasnews.com/wp-content/uploads/2012/10/FAA-UAS-Conops-Version-2-0-1.pdf.

Federal Aviation Administration. (2013). Integration of Civil Unmanned Aircraft Systems (UAS) in the National Airspace System (NAS) Roadmap. Retrieved from http://www.faa.gov/uas/media/uas_roadmap_2013.pdf

Federal Aviation Administration. (2013). Operational Use of Flight Path Management Systems: Final Report of the Performance-based Operations Aviation Rulemaking Committee. Retrieved from http://www.faa.gov/about/office_org/headquarters_offices/avs/offices/afs/afs400/parc/parc_reco/media/2013/130908_parc_fltdawg_final_report_recommendations.pdf

Federal Aviation Administration. (2015). HF-STD-001A.

Feigh, K. M., & Pritchett, A. R. (2014). Requirements for Effective Function Allocation A Critical Review. Journal of Cognitive Engineering and Decision Making, 8(1), 23-32.

Fern, L., Kenny, C. A., Shively, R. J., & Johnson, W. (2012). UAS integration into the NAS: an examination of baseline compliance in the current airspace system. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Fern, L., Rorie, R. C., Pack, J. S., Shively, R. J., & Draper, M. H. (2015). An evaluation of Detect and Avoid (DAA) displays for unmanned aircraft systems: The effect of information level and display location on pilot performance. Paper presented at the Proceedings of 15th AIAA Aviation Technology, Integration, and Operations Conference.

Fern, L., Rorie, R. C., & Shively, R. J. (2014). NASA's UAS Integration into the NAS A Report on the Human Systems Integration Phase 1 Simulation Activities. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Fern, L., Rorie, R. C., & Shively, R. J. (2014). UAS contingency management: the effect of different procedures on ATC in civil airspace operations. Paper presented at the Proceedings of the 14th Annual AIAA Aviation, Technology, Integration and Operations Conference.

Fern, L., & Shively, J. (2011). Designing airspace displays to support rapid immersion for UAS handoffs. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Fern, L., & Shively, R. J. (2009). A comparison of varying levels of automation on the supervisory control of multiple UASs. Paper presented at the AUVSI Unmanned Systems North America Conference 2009, August 10, 2009 - August 13, 2009, Washington, DC.

Fitts, P. M. (1951). Human engineering for an effective air-navigation and traffic-control system. Washington, D.C.: National Research Council.

Flach, J., Venero, P., Hughes, T., & Rowe, A. J. (2013). Supervisory control information management research (scimr). Retrieved from

Fortmann, F., & Mengeringhausen, T. (2014). Development and Evaluation of an Assistant System to Aid Monitoring Behavior during Multi-UAV Supervisory Control: Experiences from the D3CoS Project. Paper presented at the Proceedings of the 2014 European Conference on Cognitive Ergonomics, Vienna, Austria.

Frey, A., & Hanti, T. (2015). Expanding the operational range of UAS with an onboard supervisory instance. Paper presented at the Digital Avionics Systems Conference (DASC), 2015 IEEE/AIAA 34th.

Friedman-Berg, F., Rein, J., & Racine, N. (2014). Minimum visual information requirements for detect and avoid in unmanned aircraft systems. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Frost, S., Goebel, K., & Celaya, J. (2012). A Briefing on Metrics and Risks for Autonomous Decision-making in Aerospace Applications. Infotech@ Aerospace 2012, 2402.

Gandhi, N., Richards, N. D., & Bateman, A. J. (2012). Desktop simulator demonstration of a joint human/automated upset recovery system. Paper presented at the AIAA Guidance, Navigation, and Control Conference 2012, August 13, 2012 - August 16, 2012, Minneapolis, MN,.

Garvey, J. M., Kehoe, B., Basso, B., Godwin, M. F., Wood, J., Love, J., . . . Karl Hedrick, J. (2011). An autonomous unmanned aerial vehicle system for sensing and tracking. Paper presented at the AIAA Infotech at Aerospace Conference and Exhibit 2011, March 29, 2011 - March 31, 2011, St. Louis, MO.

Ghatas, R. W. (2011). The effects of system reliability and time pressure on unoccupied aircraft systems operator performance and mental workload. (M.S.), Embry-Riddle Aeronautical University. Engineering Village database.

Goldman, R. P., Miller, C. A., & Funk, H. B. (2003). A Markov Decision Process Approach to Human/Machine Function Al-location in Optionally Piloted Vehicles.

Gong, C., Girard, A., & Wang, W. (2010). Stochastic approximation to optimize the performance of human operators. Paper presented at the 2010 American Control Conference, ACC 2010, June 30, 2010 - July 2, 2010, Baltimore, MD.

Goodrich, K., Schutte, P., & Williams, R. (2011). Haptic-multimodal flight control system update. Paper presented at the Proceedings of 11th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference.

Goodrich, M., & Cummings, M. L. (2015). Human factors perspective on next generation unmanned aerial systems Handbook of Unmanned Aerial Vehicles (pp. 2405-2423): Springer.

Gupta, S. G., Ghonge, M. M., & Jawandhiya, P. (2013). Review of unmanned aircraft system (UAS). technology, 2(4).

Guznov, S., Matthews, G., Funke, G., & Dukes, A. (2011). Use of the RoboFlag synthetic task environment to investigate workload and stress responses in UAV operation. Behavior research methods, 43(3), 771-780.

Hardman, N., Colombi, J., Jacques, D., Hill, R. R., & Miller, J. E. (2009). An evaluation of collision avoidance technologies using empirical function allocation. Int J Appl Aviat Stud, 9, 133-154.

Harriott, C. E., & Adams, J. A. (2013). Modeling Human Performance for Human–Robot Systems. Reviews of human factors and ergonomics, 9(1), 94-130.

Hobbs, A., & Lyall, B. (2015). Human Factors Guidelines for Unmanned Aircraft System Ground Control Stations. Retrieved from http://humanfactors.arc.nasa.gov/publications/GCS_HF%20_Prelim_Guidelines_Hobbs_Lyall.pdf

Hobbs, A., & Shively, R. J. (2013). Human Factors Guidelines for UAS in the National Airspace System. Proceedings of Association for Unmanned Vehicle Systems International (AUVSI), 12, 15.

Hopcroft, R., Burchat, E., & Vince, J. (2006). Unmanned aerial vehicles for maritime patrol: human factors issues. Retrieved from

Hottman, S. B., Hansen, K., & Berry, M. (2009). Literature review on detect, sense, and avoid technology for unmanned aircraft systems. Retrieved from http://www.tc.faa.gov/its/worldpac/techrpt/ar0841.pdf.

Hou, M., & Kobierski, R. D. (2005). Performance modeling of agent-aided operator-interface interaction for the control of multiple UAVs. Paper presented at the IEEE Systems, Man and Cybernetics Society, Proceedings - 2005 International Conference on Systems, Man and Cybernetics, October 10, 2005 - October 12, 2005, Waikoloa, HI.

Hou, M., Kobierski, R. D., & Herdman, C. (2006). Design and evaluation of intelligent adaptive operator interfaces for the control of multiple UAVs. Paper presented at the R. Taylor & H. Ruck (Chairs), Human factors of uninhabited military vehicles as force multipliers. Presented at NATO RTO Human Factors and Medicine Panel (HFM) 135 Symposium, Biarritz, France.

International Civil Aviation Organization. (2005). Global Air Traffic Management Operational Concept. Retrieved from

Israelsen, J., Beall, M., Bareiss, D., Stuart, D., Keeney, E., & van den Berg, J. (2014). Automatic collision avoidance for manually tele-operated unmanned aerial vehicles. Paper presented at the Robotics and Automation (ICRA), 2014 IEEE International Conference on.

Izzetoglu, K., Ayaz, H., Hing, J. T., Shewokis, P. A., Bunce, S. C., Oh, P., & Onaral, B. (2015). Uav operators workload assessment by optical brain imaging technology (fnir) Handbook of Unmanned Aerial Vehicles (pp. 2475-2500): Springer.

Jackson, K. F. (2012). Development and evaluation of a collision avoidance system for supervisory control of a micro aerial vehicle. Massachusetts Institute of Technology. Google Scholar database.

Jamieson, G. A. (2006). Developing Human-Machine Interfaces to Support Monitoring of UAV Automation. Retrieved from

Jarasch, G., & Schulte, A. (2008). Satisfying integrity requirements for highly automated uav systems by a systems engineering approach to Cognitive Automation. Paper presented at the 2008 IEEE/AIAA 27th Digital Avionics Systems Conference, DASC 2008, October 26, 2008 - October 30, 2008, St. Paul, MN.

Jenkins, D. P. (2012). Using cognitive work analysis to describe the role of UAVs in military operations. Theoretical Issues In Ergonomics Science, 13(3), 335-357. doi:10.1080/1463922X.2010.506560

Jin, Y., Liao, Y., Minai, A. A., & Polycarpou, M. M. (2006). Balancing search and target response in cooperative unmanned aerial vehicle (UAV) teams. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 36(3), 571-587. doi:10.1109/TSMCB.2005.861881

Johnson, R., Leen, M., & Goldberg, D. (2007). Testing adaptive levels of automation (ALOA) for UAV supervisory control (Technical Report AFRL-HE-WP-TR-2007-0068). Air Force Research Laboratory.

Joint Planning and Development Office. (2012). Research, Development and Demonstration Roadmap: Version.

Joint Planning and Development Office. (2013). Unmanned aircraft systems (UAS) comprehensive plan–a report on the nation's UAS path forward. Retrieved from http://www.faa.gov/about/office_org/headquarters_offices/agi/reports/media/uas_comprehensive_plan.pdf

Jones, H. L., Frew, E. W., Woodley, B. R., & Rock, S. M. (2001). Human-Vehicle Interface for Semi-Autonomous Operation of Uninhabited Aero Vehicles.

Joslin, R. E. (2015). Situation Awareness Issues in Unmanned Aircraft Systems Accidents and Incidents. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Kaber, D. B., & Endsley, M. R. (1997). Out-of-the-loop performance problems and the use of intermediate levels of automation for improved control system functioning and safety. Process Safety Progress, 16(3), 126-131.

Kaber, D. B., & Prinzel III, L. J. (2006). Adaptive and Adaptable Automation Design: A Critical Review of the Literature and Recommendations for Future Research.

Karwowski, W., Haas, M., & Salvendy, G. (2006). A Review and Reappraisal of Adaptive Human-Computer Interfaces in Complex Control Systems. Retrieved from http://www.dtic.mil/cgi-bin/GetTRDoc?Location=U2&doc=GetTRDoc.pdf&AD=ADA459269

Kaste, K., Archer, J., Neville, K., Blickensderfer, B., & Luxion, S. (2012). An analysis of FAA certification regulations and guidelines for evaluating the unmanned aircraft human-machine interface: Lost link. Paper presented at the Systems and Information Design Symposium (SIEDS), 2012 IEEE.

Katrein, S. P. (2015). The Effect of Stages and Levels of Automation and Reliability on Workload and Performance for Remotely Piloted Aircraft Operations. DTIC Document. Retrieved from http://www.dtic.mil/cgi-bin/GetTRDoc?Location=U2&doc=GetTRDoc.pdf&AD=ADA616426 Defense Technical Information Center database.

Kenny, C., & Fern, L. (2012). Varying levels of automation on UAS operator responses to traffic resolution advisories in civil airspace. Advances in human aspects of aviation, 279-288.

Kenny, C., Shively, R. J., & Jordan, K. (2014). Unmanned Aircraft System (UAS) Delegation of Separation in NextGen Airspace. Retrieved from http://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20140017682.pdf

Kenny, C. A. (2013). Unmanned aircraft system (UAS) delegation of separation in NextGen airspace.

Kirlik, A. (1993). Modeling strategic behavior in human-automation interaction: Why an" aid" can (and should) go unused. Human Factors: The Journal of the Human Factors and Ergonomics Society, 35(2), 221-242.

Korteling, J., & Van der Borg, W. (1997). Partial camera automation in an unmanned air vehicle. Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 27(2), 256-262.

Lam, T. M., Mulder, M., & van Paassen, M. M. (2007). Haptic Interface For UAV Collision Avoidance. The International Journal of Aviation Psychology, 17(2), 167-195. doi:10.1080/10508410701328649

Lee, J., & Moray, N. (1992). Trust, control strategies and allocation of function in human-machine systems. Ergonomics, 35(10), 1243-1270.

Lee, S. M., & Mueller, E. R. (2013). A systems-based approach to functional decomposition and allocation for developing UAS separation assurance concepts. Paper presented at the 2013 Aviation Technology, Integration, and Operations Conference, August 12, 2013 - August 14, 2013, Los Angeles, CA.

Linegang, M., Haimson, C., MacMillan, J., & Freeman, J. (2003). Human control in mixed-initiative systems: lessons from the MICA-SHARC program. Paper presented at the SMC '03 Conference Proceedings. 2003 IEEE International Conference on Systems, Man and Cybernetics, 5-8 Oct. 2003, Piscataway, NJ, USA.

Liu, D., Jaramillo, M., & Vincenzi, D. (2015). The Effects of System Reliability and Task Uncertainty on Autonomous Unmanned Aerial Vehicle Operator Performance under High Time Pressure. Human Factors and Ergonomics in Manufacturing & Service Industries, 25(5), 515-522.

Liu, D., Reynolds, C., Vincenzi, D., & Doherty, S. (2013). Effect of pilot and air traffic control experiences and automation management strategies on unmanned aircraft systems mission task performance. Human Factors and Ergonomics In Manufacturing, 23(5), 424-435. doi:10.1002/hfm.20330

Liu, D., Wasson, R., & Vincenzi, D. A. (2009). Effects of system automation management strategies and multi-mission operator-to-vehicle ratio on operator performance in UAV systems. Journal of Intelligent and Robotic Systems: Theory and Applications, 54(5), 795-810. doi:10.1007/s10846-008-9288-4

Maloney, P., & Gilson, S. (2012). Networked Enabled Operations Spiral II UAS Demonstration 5: Simulation Report. Retrieved from

Mathe, K., & Buoniu, L. (2015). Vision and control for UAVs: A survey of general methods and of inexpensive platforms for infrastructure inspection. Sensors (Switzerland), 15(7), 14887-14916. doi:10.3390/s150714887

McCarley, J. S., & Wickens, C. D. (2005). Human factors implications of UAVs in the national airspace: University of Illinois at Urbana-Champaign, Aviation Human Factors Division.

McCauley, M. E., & Matsangas, P. G. (2004). Human systems integration and automation issues in small unmanned aerial vehicles.

McKendrick, R., Shaw, T., De Visser, E., Saqer, H., Kidwell, B., & Parasuraman, R. (2014). Team performance in networked supervisory control of unmanned air vehicles: Effects of automation, working memory, and communication content. Human Factors, 56(3), 463-475. doi:10.1177/0018720813496269

Miller, C. A., Draper, M., Hamell, J. D., Calhoun, G., Barry, T., & Ruff, H. (2013). Enabling dynamic delegation interactions with multiple unmanned vehicles; flexibility from top to bottom Engineering Psychology and Cognitive Ergonomics. Applications and Services (pp. 282-291): Springer.

Miller, C. A., Hamell, J., Barry, T., Ruff, H., Draper, M. H., & Calhoun, G. L. (2012). Adaptable operator-automation interface for future unmanned Aerial Systems Control: Development of a Highly Flexible delegation concept demonstration. Paper presented at the AIAA Infotech at Aerospace Conference and Exhibit 2012, June 19, 2012 - June 21, 2012, Garden Grove, CA.

Miller, C. A., & Parasuraman, R. (2003). Beyond levels of automation: An architecture for more flexible human-automation collaboration. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Miller, C. A., & Parasuraman, R. (2007). Designing for flexible interaction between humans and automation: Delegation interfaces for supervisory control. Human Factors: The Journal of the Human Factors and Ergonomics Society, 49(1), 57-75.

Miller, C. A., Shaw, T., Emfield, A., Hamell, J., Parasuraman, R., & Musliner, D. (2011). Delegating to Automation Performance, Complacency and Bias Effects under Non-Optimal Conditions. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Miller, M. E., Peterson, G., Langhals, B., & Bindewald, J. (2014). Workload-Adaptive Human Interface to Aid Robust Decision Making in Human-System Interface. Year 1 Report. Retrieved from

Monk, K., Shively, R. J., Fern, L., & Rorie, R. C. (2015). Effects of Display Location and Information Level on UAS Pilot Assessments of a Detect and Avoid System. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Moore, B. J., Finke, J., & Passino, K. M. (2009). Optimal allocation of heterogeneous resources in cooperative control scenarios. Automatica, 45(3), 711-715. doi:10.1016/j.automatica.2008.09.007

Morse, B. S., Thornton, D., & Goodrich, M. A. (2012). Color anomaly detection and suggestion for wilderness search and rescue. Paper presented at the Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction.

Mouloua, M., Gilson, R., & Hancock, P. (2003). Human-centered design of unmanned aerial vehicles. Ergonomics in Design: The Quarterly of Human Factors Applications, 11(1), 6-11.

Murphy, J., Otto, N., & Jovic, S. (2015). UAS-NAS Integrated Human in the Loop Test Environment Report. Retrieved from

Murphy, R. R., Pratt, K. S., & Burke, J. L. (2008). Crew roles and operational protocols for rotary-wing micro-UAVs in close urban environments. Paper presented at the Proceedings of the 3rd ACM/IEEE international conference on Human robot interaction.

Mutuel, L. H., Wargo, C. A., & Difelici, J. (2015). Functional decomposition of Unmanned Aircraft Systems (UAS) for CNS capabilities in NAS integration. Paper presented at the 2015 IEEE Aerospace Conference, AERO 2015, March 7, 2015 - March 14, 2015, Big Sky, MT.

National Research Council. (2014). Autonomy Research for Civil Aviation: Toward a New Era of Flight. Washington, D.C.: National Acadamies Press.

Nehme, C. E., Crandall, J. W., & Cummings, M. (2007). An operator function taxonomy for unmanned aerial vehicle missions. Paper presented at the 12th international command and control research and technology symposium.

Nisser, T., & Westin, C. (2006). Human factors challenges in unmanned aerial vehicles (uavs): A literature review. School of Aviation of the Lund University, Ljungbyhed.

Norman, D. A. (1990). The 'problem' with automation: inappropriate feedback and interaction, not 'over-automation'. Philosophical Transactions of the Royal Society of London B: Biological Sciences, 327(1241), 585-593.

Oncu, M., & Yildiz, S. (2014). An analysis of human causal factors in Unmanned Aerial Vehicle (UAV) accidents. Retrieved from http://calhoun.nps.edu/bitstream/handle/10945/44637/14Dec_Oncu_Yildiz.pdf?sequence=1

Onnasch, L., Wickens, C. D., Li, H., & Manzey, D. (2014). Human Performance Consequences of Stages and Levels of Automation An Integrated Meta-Analysis. Human Factors: The Journal of the Human Factors and Ergonomics Society, 0018720813501549.

Oomkens, W., Mulder, M., Van Paassen, M. M., & Amelink, M. H. J. (2008). Uavs as aviators: Environment skills capability for UAVs. Paper presented at the 2008 IEEE International Conference on Systems, Man and Cybernetics, SMC 2008, October 12, 2008 - October 15, 2008, Singapore, Singapore.

Pack, J. S., Draper, M. H., Darrah, S. J., Squire, M. P., & Cooks, A. (2015). Exploring Performance Differences Between UAS Sense-and-Avoid Displays. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. Human Factors: The Journal of the Human Factors and Ergonomics Society, 39(2), 230-253.

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 30(3), 286-297.

Pastor, E., Royo, P., Santamaria, E., Prats, X., & Barrado, C. (2009). In-flight contingency management for unmanned aerial vehicles. Paper presented at the AIAA Infotech at Aerospace Conference and Exhibit and AIAA Unmanned...Unlimited Conference, April 6, 2009 - April 9, 2009, Seattle, WA.

Peschel, J. M., & Murphy, R. R. (2015). Human Interfaces in Micro and Small Unmanned Aerial Systems Handbook of Unmanned Aerial Vehicles (pp. 2389-2403): Springer.

Pestana, M. E. (2011). Flying Unmanned Aircraft: A Pilot's Perspective. Paper presented at the em AIAA Infotech at Aerospace Conference and Exhibit.

Prabhala, S. V., Gallimore, J. J., & Narayanan, S. (2003). Emerging areas: urban operations and UCAVs: human effectiveness issues in simulated uninhabited combat aerial vehicles. Paper presented at the Proceedings of the 35th conference on Winter simulation: driving innovation, New Orleans, Louisiana.

Prinet, J. C., Terhune, A., & Sarter, N. B. (2012). Supporting Dynamic Re-Planning In Multiple Uav Control: A Comparison of 3 Levels of Automation. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Pritchett, A. R. (2009). Aviation automation: General perspectives and specific guidance for the design of modes and alerts. Reviews of human factors and ergonomics, 5(1), 82-113.

Pritchett, A. R., Kim, S. Y., & Feigh, K. M. (2014). Measuring human-automation function allocation. Journal of Cognitive Engineering and Decision Making, 8(1), 52-77.

Pritchett, A. R., Kim, S. Y., & Feigh, K. M. (2014). Modeling human–automation function allocation. Journal of Cognitive Engineering and Decision Making, 8(1), 33-51.

Rash, C. E., LeDuc, P. A., & Manning, S. D. (2006). Human factors in US military unmanned aerial vehicle accidents Human Factors of Remotely Operated Vehicles (Vol. 7, pp. 117-131).

Riley, J., Murphy, R., & Endsley, M. (2006). Situation Awareness in the Control of Unmanned Ground Vehicles☆. 7, 359-371. doi:10.1016/s1479-3601(05)07025-6

Riley, J., Strater, L., Chappell, S., Connors, E., & Endsley, M. (2010). Situation awareness in human-robot interaction: Challenges and user interface requirements (pp. 173-191): Burlington, VT: Ashgate.

Riley, J. M., & Endsley, M. R. (2005). Situation awareness in HRI with collaborating remotely piloted vehicles. Paper presented at the 49th Annual Meeting of the Human Factors and Ergonomics Society, HFES 2005, September 26, 2005 - September 30, 2005, Orlando, FL.

Rorie, R. C., & Fern, L. (2014). UAS measured response the effect of GCS control mode interfaces on pilot ability to comply with ATC clearances. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Rorie, R. C., & Fern, L. (2015). The impact of integrated maneuver guidance information on UAS pilots performing the Detect and Avoid task. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Rorie, R. C., Fern, L., & Shively, J. (2016). The Impact of Suggestive Maneuver Guidance on UAS Pilot Performing the Detect and Avoid Function AIAA Infotech@ Aerospace (pp. 1002).

RTCA Inc. (2010). Operational services and environmental definition (OSED) for unmanned aircraft systems (uas). Retrieved from http://www.rtca.org

Rudnick, G., Clauß, S., & Schulte, A. (2014). Flight testing of agent supervisory control on heterogeneous unmanned aerial system platforms. Paper presented at the 2014 IEEE/AIAA 33rd Digital Avionics Systems Conference (DASC), 5-9 Oct. 2014, Piscataway, NJ, USA.

Ruff, H. A., Draper, M. H., Lu, L. G., Poole, M. R., & Repperger, D. W. (2000). Haptic feedback as a supplemental method of alerting UAV operators to the onset of turbulence. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Ruff, H. A., Narayanan, S., & Draper, M. H. (2002). Human interaction with levels of automation and decision-aid fidelity in the supervisory control of multiple simulated unmanned air vehicles. Presence: Teleoperators and virtual environments, 11(4), 335-351.

Ruiz, J. J., Escalera, M. A., Viguria, A., & Ollero, A. (2015, 23-25 Nov. 2015). A simulation framework to validate the use of head-mounted displays and tablets for information exchange with the UAV safety pilot. Paper presented at the 2015 Workshop on Research, Education and Development of Unmanned Aerial Systems (RED-UAS).

Santiago, C., & Mueller, E. R. (2015). Pilot Evaluation of a UAS Detect-and-Avoid System's Effectiveness in Remaining Well Clear. Paper presented at the Eleventh UAS/Europe Air Traffic Management Research and Development Seminar (ATM2015).

Sarter, N. B., & Woods, D. D. (1995). How in the world did we ever get into that mode? Mode error and awareness in supervisory control. Human Factors: The Journal of the Human Factors and Ergonomics Society, 37(1), 5-19.

Saunders, J. B., Rasmussen, S. J., & Schumacher, C. J. (2007). Combining collision avoidance and operator workload reduction with cooperative task assignment and path planning. Paper presented at the 2007 American Control Conference, 9-13 July 2007, Piscataway, NJ, USA.

Schulte, A. (2002). Cognitive automation for tactical mission management: concept and prototype evaluation in flight simulator trials. Cognition, Technology & Work, 4(3), 146-159. doi:10.1007/s101110200014

Schulte, A., Donath, D., & Honecker, F. (2015). Human-System Interaction Analysis for Military Pilot Activity and Mental Workload Determination. Paper presented at the 2015 IEEE International Conference on Systems, Man and Cybernetics (SMC), 9-12 Oct. 2015, Piscataway, NJ, USA.

Schumann, J. M., Rozier, K. Y., Reinbacher, T., Mengshoel, O. J., Mbaya, T., & Ippolito, C. (2015). Towards real-time, on-board, hardware-supported sensor and software health management for unmanned aerial systems. International Journal of Prognostics and Health Management, 6.

Scott, S. D., Mercier, S., Cummings, M., & Wang, E. (2006). Assisting interruption recovery in supervisory control of multiple UAVs. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Shaw, T., Emfield, A., Garcia, A., De Visser, E., Miller, C., Parasuraman, R., & Fern, L. (2010). Evaluating the benefits and potential costs of automation delegation for supervisory control of multiple UAVs. Paper presented at the 54th Human Factors and Ergonomics Society Annual Meeting 2010, HFES 2010, September 27, 2010 - October 1, 2010, San Francisco, CA.

Sheridan, T. B., & Parasuraman, R. (2005). Human-automation interaction. Reviews of human factors and ergonomics, 1(1), 89-129.

Shively, R., Brasil, C., & Flaherty, S. (2007). Alternative UAV sensor control: leveraging gaming skill. Paper presented at the Proceedings of the ISAP'07 Conference.

Shively, R. J., Hobbs, A., Lyall, B., & Rorie, C. (2015). Human Performance Considerations for Remotely Piloted Aircraft Systems (RPAS).

Shively, R. J., Neiswander, G. M., & Fern, L. (2011). Manned-unmanned teaming: Delegation control of Unmanned Aerial Systems (UAS). Paper presented at the 67th American Helicopter Society International Annual Forum 2011, May 3, 2011 - May 5, 2011, Virginia Beach, VA.

Shively, R. J., Vu, K. P. L., & Buker, T. J. (2013). Unmanned Aircraft System Response to Air Traffic Control Clearances: Measured Response. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 57(1), 31-35. doi:10.1177/1541931213571009

Sidewater, E., Archbold, S., & Urioste, M. (2005). Command and Control of tactical UAVs; optimizing the probability of detection. Paper presented at the AUVSI's Unmanned Systems North America 2005, June 28, 2005 - June 30, 2005, Baltimore, MD.

Simmons, G. G., Liu, D., Xuedong, D., & Vincenzi, D. A. (2008). Effect of pilot experience and automation strategy on unmanned aerial vehicle mission performance. Paper presented at the IIE Annual Conference and Expo 2008, May 17, 2008 - May 21, 2008, Vancouver, BC, Canada.

Smallman, H. S., John, M. S., & Cowen, M. B. (2004). Limits of display realism: human factors issues in visualizing the common operational picture. Visualisation and the Common Operational Picture, 16-11.

Spravka, J. J., Moisio, D. A., & Payton, M. G. (2005). Unmanned Air Vehicles: A New Age in Human Factors Evaluations. Retrieved from

St. John, M. F., & King, M. A. (2010). The four-second supervisor: multi-tasking supervision and its support. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Stanard, T., Bearden, G., & Rothwell, C. (2013). A cognitive task analysis to elicit preliminary requirements for an automated UAV verification planning system. Paper presented at the 57th Human Factors and Ergonomics Society Annual Meeting - 2013, HFES 2013, September 30, 2013 - October 4, 2013, San Diego, CA.

Stansbury, R. S., Vyas, M. A., & Wilson, T. A. (2008). A survey of UAS technologies for command, control, and communication (C3). Journal of Intelligent and Robotic Systems, 54(1-3), 61-78.

Stark, B., Coopmans, C., & Chen, Y. (2012). A framework for analyzing human factors in unmanned aerial systems. Paper presented at the 2012 5th International Symposium on Resilient Control Systems, ISRCS 2012, August 14, 2012 - August 16, 2012, Salt Lake City, UT.

Steinberg, M. (2006). Intelligent autonomy for unmanned naval vehicles. Paper presented at the Unmanned Systems Technology VIII, April 17, 2006 - April 20, 2006, Kissimmee, FL.

Strater, L., Connors, E., Endsley, M., Johnson, R., Leen, M., & Goldberg, D. (2007). Integrated Collaborative Control (IC2) of Unmanned Vehicle Systems. Retrieved from

Tang, L., Kacprzynski, G. J., Goebel, K., Saxena, A., Saha, B., & Vachtsevanos, G. (2008). Prognostics-enhanced automated contingency management for advanced autonomous systems. Paper presented at the 2008 International Conference on Prognostics and Health Management, PHM 2008, October 6, 2008 - October 9, 2008, Denver.

Theunissen, E., Tadema, J., & Goossens, A. (2009). Exploring network enabled concepts for U (C) AV payload driven navigation. Paper presented at the Digital Avionics Systems Conference, 2009. DASC'09. IEEE/AIAA 28th.

Trujillo, A. C., Ghatas, R. W., Mcadaragh, R., Burdette, D. W., Comstock, J. R., Hempley, L. E., & Fan, H. (2015). Small Unmanned Aircraft Systems Integration into the National Airspace System Visual-Line-of-Sight Human-in-the-Loop Experiment.

Tso, K. S., Tharp, G. K., Tai, A. T., Draper, M. H., Calhoun, G. L., & Ruff, H. A. (2003). A human factors testbed for command and control of unmanned air vehicles. Paper presented at the Digital Avionics Systems Conference, 2003. DASC'03. The 22nd.

Tvaryanas, A. P. (2006). Human factors considerations in migration of unmanned aircraft system (UAS) operator control. Retrieved from http://www.wpafb.af.mil/shared/media/document/AFD-090121-046.pdf

Tvaryanas, A. P. (2006). Human systems integration in remotely piloted aircraft operations. Aviation, space, and environmental medicine, 77(12), 1278-1282.

Tvaryanas, A. P., Thompson, W. T., & Constable, S. H. (2005). The US Military Unmanned Aerial Vehicle (UAV) Experience: Evidence-Based Human Systems Integration Lessons Learned.

Tvaryanas, A. P., Thompson, W. T., & Constable, S. H. (2006). Human factors in remotely piloted aircraft operations: HFACS analysis of 221 mishaps over 10 years. Aviation, space, and environmental medicine, 77(7), 724-732.

Tweedale, J. W., & Gonano, D. (2014). Enhancing the dgree of autonomy on a 'Tier 1' unmanned aerial vehicle using a visual landing framework. Paper presented at the International Conference on Knowledge-Based and Intelligent Information and Engineering Systems, KES 2014, September 15, 2014 - September 17, 2014, Gdynia, Poland.

Uhrmann, J., & Schulte, A. (2012). Concept, Design and Evaluation of Cognitive Task-based UAV Guidance. International Journal On Advances in Intelligent Systems 5.1 and, 2.

United States Department of Defense. (2011). Unmanned Aircraft System Airspace Integration Plan. Retrieved from

United States Department of Defense. (2012). Unmanned Aircraft Systems Ground Control Station Human-Machine Interface: Development and Standardization Guide. Retrieved from

United States Department of Defense. (2015). Unmanned Aircraft Systems Airspace Integration Joint Test: UAS National Airspace System Flight Operations Standardized Procedures. Retrieved from

Valimont, R. B., & Chappell, S. L. (2011). Look where I'm going and go where I'm looking: Camera-up map for unmanned aerial vehicles. Paper presented at the Human-Robot Interaction (HRI), 2011 6th ACM/IEEE International Conference on.

Van Dijk, H., & De Reus, A. (2010). Automation and multiple ua control. Paper presented at the 27th Congress of the International Council of the Aeronautical Sciences 2010, ICAS 2010, September 19, 2010 - September 24, 2010, Nice, France.

Van Ginkel, H. T. A., De Vries, M. F. L., Koeners, J. J. M., & Theunissen, E. (2006). Flexible authority allocation in unmanned aerial vehicles. Paper presented at the 50th Annual Meeting of the Human Factors and Ergonomics Society, HFES 2006, October 16, 2006 - October 20, 2006, San Francisco, CA.

Van Maanen, P.-P., Holleman, B., Kerbusch, P., Van Der Kleij, R., Smets, N., Smit, S., & Rakhorst-Oudendijk, M. (2014). Integration of functions within STUAS operator crew on board royal Netherlands Navy ships. Paper presented at the 2014 International Conference on Unmanned Aircraft Systems, ICUAS 2014, May 27, 2014 - May 30, 2014, Orlando, FL.

van Paassen, M. M., Bolton, M. L., & Jimenez, N. (2014). Checking formal verification models for human-automation interaction. Paper presented at the Systems, Man and Cybernetics (SMC), 2014 IEEE International Conference on.

Vincenzi, D. A., Mouloua, M., & Hancock, P. A. (2004). Human Performance, Situation Awareness and Automation: Current Research and Trends: HPSAA II (Vol. 2): Psychology Press.

Vu, K.-P. L., Morales, G., Chiappe, D., Strybel, T. Z., Battiste, V., Shively, J., & Buker, T. J. (2013). Influence of UAS pilot communication and execution delay on controller's acceptability ratings of UAS-ATC interactions. Paper presented at the Digital Avionics Systems Conference (DASC), 2013 IEEE/AIAA 32nd.

Wasson, R., Liu, D., & Macchiarella, D. (2007). The effect of level of automation and number of UAVs on operator performance in UAV systems. Paper presented at the IIE Annual Conference and Expo 2007 - Industrial Engineering's Critical Role in a Flat World, May 19, 2007 - May 23, 2007, Nashville, TN.

Wickens, C. D., & Dixon, S. (2002). Workload demands of remotely piloted vehicle supervision and control: (1) single vehicle performance. Retrieved from http://www.dtic.mil/dtic/tr/fulltext/u2/a496813.pdf

Wickens, C. D., Dixon, S., & Chang, D. (2003). Using interference models to predict performance in a multiple-task UAV environment-2 UAVs. Retrieved from

Wickens, C. D., Dixon, S. R., & Ambinder, M. S. (2006). 15. Workload and Automation Reliability in Unmanned Air Vehicles. Human Factors of Remotely Operated Vehicles, 7, 209-222.

Wickens, C. D., Dixon, S. R., & Johnson, N. (2006). Imperfect diagnostic automation: an experimental examination of priorities and threshold setting. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Wickens, C. D., Li, H., Santamaria, A., Sebok, A., & Sarter, N. B. (2010). Stages and levels of automation: An integrated meta-analysis. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Williams, K. W. (2004). A summary of unmanned aircraft accident/incident data: Human factors implications. Retrieved from http://www.dtic.mil/get-tr-doc/pdf?AD=ADA460102

Williams, K. W. (2006). Human factors implications of unmanned aircraft accidents: Flight-control problems. Retrieved from http://ntl.bts.gov/lib/34000/34000/34063/GetTRDoc.pdf

Williams, K. W. (2007). An assessment of pilot control interfaces for unmanned aircraft. Retrieved from http://www.faa.gov/data_research/research/med_humanfacs/oamtechreports/2000s/media/200708.pdf

Williams, K. W. (2007). Unmanned aircraft pilot medical certification requirements. Retrieved from https://fas.org/irp/program/collect/ua-pilot.pdf

Williams, K. W. (2008). Documentation of sensory information in the operation of unmanned aircraft systems. Retrieved from http://www.faa.gov/data_research/research/med_humanfacs/oamtechreports/2000s/media/200823.pdf

Williams, K. W. (2012). An Investigation of Sensory Information, Levels of Automation, and Piloting Experience on Unmanned Aircraft Pilot Performance. Retrieved from http://www.faa.gov/data_research/research/med_humanfacs/oamtechreports/2010s/media/201204.pdf

Williams, K. W., & Gildea, K. M. (2014). A Review of Research Related to Unmanned Aircraft System Visual Observers. Retrieved from http://libraryonline.erau.edu/online-full-text/faa-aviation-medicine-reports/AM14-09.pdf

Wilson, G. F., & Russell, C. A. (2007). Performance enhancement in an uninhabited air vehicle task using psychophysiologically determined adaptive aiding. Human Factors, 49(6), 1005-1018. doi:10.1518/001872007X249875

Wing, D., Prevot, T., Morey, S., Lewis, T., Martin, L., Johnson, S., . . . Sheth-Chandra, M. (2013). Pilot and controller evaluations of separation function allocation in air traffic management.

Woodly, R. S., Gosnell, M., Gallimore, J. J., & Prabhala, S. (2007). Agents with personality: Human operator assistants. Paper presented at the Summer Computer Simulation Conference 2007, SCSC 2007, Part of the 2007 Summer Simulation Multiconference, SummerSim 2007, July 15, 2007 - July 18, 2007, San Diego, CA.

Yeh, M., & Wickens, C. D. (2001). Display signaling in augmented reality: Effects of cue reliability and image realism on attention allocation and trust calibration. Human Factors: The Journal of the Human Factors and Ergonomics Society, 43(3), 355-365.

Yuan, X., Histon, J. M., & Waslander, S. (2014). Survey of Operators' Information Requirements on Individually Operated Unmanned Aircraft Systems. Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

8. APPENDIX A3: ANNOTATED BIBLIOGRAPHY

1. Bainbridge, L. (1983). Ironies of automation. *Automatica, 19*(6), 775-779.

The paper presents the various issues associated with automating tasks, and potential approaches to solutions to alleviate those problems. Limitations to the implementation of automation include operator manual control skills (particularly during a takeover of authority), cognitive skills (e.g., long-term knowledge and working storage), monitoring (effective human vigilance does not last more than a half hour), and operator attitudes. Regarding approaches to solutions for these problems, monitoring/vigilance problems require alarms and displays to alert the operator of an off-nominal event. However, care needs to be taken to ensure that alarms and displays are effective and engender trust in the operator. For failures that require fast response (i.e., not enough time for the operator to learn the system state), automation should respond to the off-nominal event. With failures that do not require fast responses, it may be possible for the operator to deal with the event with overlearned manual responses, but this requires frequent practice on a high-fidelity simulator. This facilitates the maintenance of operator manual skills, but unknown faults cannot be simulated. Overall, automation has the ability to reduce human workload, but care needs to be taken to ensure that automation of functions does not make a job more difficult for the operator.

2. Barnes, M. J., Knapp, B. G., Tillman, B. W., Walters, B. A., & Velicki, D. (2000). *Crew systems analysis of unmanned aerial vehicle (UAV) future job and tasking environments*. Retrieved from http://www.dtic.mil/dtic/tr/fulltext/u2/a374230.pdf

Three investigations are reported, with the overall objective to understand the crew environment and soldier performance issues related to future UAS systems. The three major issues addressed were (1) the importance of using rated aviators as UAS operatorss, (2) the use of imagery specialists and intelligence analysts as adjunct crew members, and (3) the potential use of automation to assist in future crew functions. Regarding the importance of using rated aviators, subjective data were collected from Army aviators to determine the important cognitive skills required for the internal pilot (IP) and external pilot (EP) positions for a Hunter UAS, along with tracking scores collected for an EP training course and UAS flight incident reports. Results revealed little evidence for the need of rated aviator skills for either the IP or the EP. The results were confirmed via SME discussions, with the caveat that this may not be true for other UASs, which may be controlled more similarly to a manned aircraft (e.g., Predator). Regarding the use of imagery specialists, the results revealed that use of imagery specialists likely do not increase payload image processing performance beyond the traditional UAS flight crew. Finally, regarding UAS automation, a MicroSaint simulation model was constructed for the Outrider UAS platform to model crew workload issues on the visual, auditory, cognitive, and perceptual (VACP) scale. A set of tasks were recommended as the best candidates for automation. In general, the operators did not want fully automated systems; they instead preferred the decision making to remain with the operator, with automation providing workload reduction.

3. Billings, C. E. (1996). Human-centered aviation automation: Principles and guidelines.

This book outlines the history of automation in aviation systems and some of the current issues (as of 1996) with aviation automation systems. Included is a review of relevant aircraft incidents related to failure in the interaction between the flight crew and the automation. The author stresses the importance of a human-centered approach in the design and implementation of aviation automation systems. A series of requirements and guidelines are given for aviation automation, as well as issues for future aviation automation.

4. Calhoun, G., Draper, M., Miller, C., Ruff, H., Breeden, C., & Hamell, J. (2013). *Adaptable automation interface for multi-unmanned aerial systems control: Preliminary usability evaluation.* Paper presented at the 57th Human Factors and Ergonomics Society Annual Meeting - 2013, HFES 2013, September 30, 2013 - October 4, 2013, San Diego, CA.

A usability analysis was conducted on an interface allowing the participant to switch between three control interfaces for conducting a UAS task. The task involved the control of three UASs utilizing a think-aloud paradigm during the task, followed by debriefing questionnaires on the potential value and usability of the interface. In general, the participants rated the interface very high, and particularly noted that they liked the ability to switch between control modes. However, they stressed the importance of making it easier to switch between control modes.

5. Calhoun, G. L., Draper, M. H., & Ruff, H. A. (2009). *Effect of level of automation on unmanned aerial vehicle routing task.* Paper presented at the 53rd Human Factors and Ergonomics Society Annual Meeting 2009, HFES 2009, October 19, 2009 - October 23, 2009, San Antonio, TX.

The objective of the experiment was to determine the most beneficial of three LOAs for completing a routing task, supervising either one or three UAVs. In the lowest LOA, the automation provided two re-route options from which the operator chose the best option; in the intermediate level, the automation provided one re-route option from which the operator chose the best option; in the highest LOA, the automation chose the best re-route option. In some cases, the automation was imperfect, so the participant had the authority to generate his/her own route in all LOAs. In addition to re-routing due to threats, participants were also required to re-route around unidentified threats while conducting an image analysis task and monitoring system health and status. Results revealed that re-route completion time was significantly longer in the highest LOA than in the intermediate and low LOAs, but subjective ratings favored the highest LOA. In general, interfaces need to be designed to allow easy inspection and generation of routes, particularly under conditions of faulty automation.

6. Cook, M. B., & Smallman, H. S. (2013). *Human-centered command and control of future autonomous systems*. Retrieved from http://www.dtic.mil/cgi-bin/GetTRDoc?Location=U2&doc=GetTRDoc.pdf&AD=ADA588335

This paper presents the results of a task- and user-centered design approach to supervisory decision support and human-machine interface design for future autonomous systems. A total of 27 UAS SMEs participated in a three-stage interview approach, with a focus on automation during mission execution (i.e., planning, takeoff, landing, and recovery were beyond the scope of analysis). The objective of stage 1 was to define core tasks involved in UAS system operation and supervision. In stage 2, SMEs were used to specify current allocation of tasks to humans and automation, and propose future allocations. Finally, stage 3 identified information exchange between humans and automation for a subset of detection tasks. Current displays promote reactive monitoring, which is at odds with the needs of operators to monitor proactively.

7. Cook, M. B., Smallman, H. S., Lacson, F. C., & Manes, D. I. (2010). *Situation displays for dynamic UAV replanning: Intuitions and performance for display formats.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Participants conducted a task which required UAV re-planning due to closed airspace and relocated intelligence, surveillance, and reconnaissance (ISR) targets. Three display formats were tested, including a baseline two-dimensional (2D), an augmented 2D presenting restricted airspace, and a perspective three-dimensional (3D), which provided a 3D view of the augmented 2D display. The three display types manipulated the LOA of the restricted airspace presentation. The ISR task was conducted in either flat or mountainous terrain since prior research suggested that mountainous terrain was troublesome for participants to navigate around. Dependent variables included RT for correct and incorrect re-planned routes, error rate, and error severity reflected through the number of violations per trial. In flat terrain, route re-planning time was significantly slower in the baseline 2D display than the augmented 2D and 3D displays, with no difference between the latter two conditions. A similar trend was exhibited for re-planning error rate, for which the error rate was significantly higher in the baseline condition than in the remaining two. The augmented 2D display yielded the lowest error severity, followed by the 3D display, then by the baseline 2D display. In general, the augmented 2D display yielded highest performance across the objective dependent variables, but participants generally preferred the perspective 3D display.

8. Cummings, M. L. (2004). The need for command and control instant message adaptive interfaces: Lessons learned from Tactical Tomahawk human-in-the-loop simulations. *CyberPsychology & Behavior*, *7*(6), 653-661.

In a human-in-the-loop simulation in which participants were required to monitor multiple Navy Tactical Tomahawk missiles, results revealed that participants tended to fixate on the real-time secondary instant messaging task rather than the missile monitoring task, despite the fact that participants were repeatedly told that the missile monitoring task was their top priority. Correlation analyses confirmed that those who dedicated too much time to the secondary chat task experienced overall lower performance scores than those who did not engage in such behavior. This has been studied in the interruption literature since messages can interrupt operators at times of high workload. Therefore, automation may be beneficial in delaying the receipt of messages until a time when the participant has sufficient cognitive resources to process and respond to the content; although, it is not clear if there would be any unintended consequences of the institution of such automation.

9. Davis, K. D. (2008). Unmanned Aircraft Systems Operations in the US National Airspace System. *Interim Operational Approval Guidance*, 08-01.

The document presents a recommended approach to determining whether UAS may be allowed to conduct flight operations in the NAS. Currently, there are two methods to gain approval to fly an UAS in the NAS: a certificate of waiver or authorization, or the issuance of a special airworthiness certificate. Unless specifically authorized, UAS operations in other than active restricted, prohibited, or warning areas, or Class A airspace shall require visual observers, either airborne or ground-based. Use of visual observers satisfies the "see and avoid" requirement for all aircraft operating in the NAS. The pilot must hold a current instrument rating in a manned aircraft, and the pilot-in-command has final authority and responsibility for the operation and safety of flight (i.e., has authority to override automation).

10. De Vries, M. F. L., Koeners, G. J. M., Roefs, F. D., Van Ginkel, H. T. A., & Theunissen, E. (2006). *Operator support for time-critical situations: Design and evaluation.* Paper presented at the 25th DASC Digital Avionics Systems Conference - Network-Center Environment: The Impact on Avionics and Systems, October 15, 2006 - October 19, 2006, Portland, OR.

Two experiments were conducted which assessed the effects of three LOAs in experiment 1 and 2 LOAs in experiment 2 of traffic and terrain alerting/maneuvering on UAS operator SA and ability to avoid a conflict. In the first experiment, three events occurred necessitating maneuvers in each of the three runs flown by each participant, which simulated approaches and departures. Overall, there was little to no differences in conflict avoidance performance or operator SA, as the measures were relatively high across the varying LOAs. Based on the results of the first experiment, changes were made to the displays for use in the second experiment. Changes included overlay of the traffic situation information on the terrain map, directional intruder icons, a vertical profile display, and an ego-view tunnel display of the future flight path. The same procedure was employed in the second experiment, which produced significantly lower workload ratings than experiment 1, but no significant differences among the LOAs.

11. Dixon, S. R., Wickens, C. D., & Chang, D. (2005). Mission control of multiple unmanned aerial vehicles: A workload analysis. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 47*(3), 479-487.

Interviews with subject-matter experts revealed control of UAS workstations involves three major visually distributed subtasks: (a) mission completion; (b) monitoring the health of the various on-board system parameters; and (c) surveillance of the ground beneath each path to identify targets. In the experiment conducted, autopilot can handle all aspects of task (a) and an autoalert system can replace the visual monitoring associated with task (b). With these in mind, the purpose of the experiment was to assess the extent of workload overload associated with control of one and two UAVs, assess the effects of the two forms of automation, and assess the implications of these data for computational models of multi-task performance and workload overload. The experiment contained three automation conditions: baseline (mostly manual navigation), autoalert, and autopilot. Pilots flew 10 straight target-search flight legs, during which they were required to monitor the system gauges and detect system failures when they occurred. Within the single-UAV condition, there was a significant effect of automation level on tracking error, number of repeat requests for information, target of opportunity (TOO) detection rate, and system failure detection time. There was no significant effect of automation level on command target (CT) report time, CT report accuracy, TOO report time, system failure detection rate, or system failure report accuracy. For tracking error in the single-UAV condition, there was no significant difference between the baseline and autoalert conditions, but autopilot resulted in significantly better control performance (as expected, since participants did not need to manually navigate the UAV). The number of information requests decreased as a function of increasing automation; TOO detection rate was significantly higher in the autopilot condition compared to the two remaining conditions; and system failure detection time was smaller in the autoalert condition than in the remaining conditions. The results suggest that pilots prioritized tasks as follows: (1) flight control; (2) mission success; (3) system health; and (4) TOO surveillance. Pilots were able to use the auditory resources to better understand the command target instructions in a highly demanding visual environment.

12. Draper, M. H., Pack, J. S., Darrah, S. J., Moulton, S. N., & Calhoun, G. L. (2014). *Human-Machine Interface development for common airborne sense and avoid program.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

The authors give an overview of the studies and procedure that led them to define minimum information requirements for UAS detect-and-avoid (DAA) display functionality. They began with a review of existing prototypes and a review of potential intruder symbols. A static-image-based presentation revealed UAS operators to prefer visual alerts utilizing color and highlighting. Next, a survey yielded information that should be displayed to UAS operators at all times, corroborated by another review of the literature. With all of this information at hand, "basic" and "advanced" display prototypes were developed and are currently undergoing empirical evaluation via human-in-the-loop experimentation.

13. Durso, F. T., Stearman, E. J., Morrow, D. G., Mosier, K. L., Fischer, U., Pop, V. L., & Feigh, K. M. (2014). Exploring Relationships of Human-Automation Interaction Consequences on Pilots Uncovering Subsystems. *Human Factors, 57*(3), 397-406.

The paper details a structured interview approach with certified pilots to reveal the underlying latent structure of pilot interaction with flight deck automation. Pilot perception of human-automation interaction (HAI) is a function of the automation, task, context, and pilot. The authors created 48 scenarios based on recently reported aviation incidents, and asked 12 commercial airline pilots to rate on a scale of one to seven the following eleven psychological and behavioral dimensions: workload, task management, stress/nervousness, monitoring automation, cross-checking automation, awareness of the automation's state, SA, probability of an automation-related error, interaction with the automation, crew coordination, and air-ground communication. Via pairwise correlations among the subdimension ratings, three clusters emerged that may reflect subsystems of flight deck activity: workload, SA, and management. These subsystems generally corroborated prior work in the area. Monitor automation was present in all three subsystems, confirming that the human's ability to monitor automation and its relationship to workload, SA, and management is well founded.

14. Endsley, M. R., & Kiris, E. O. (1995). The out-of-the-loop performance problem and level of control in automation. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 37*(2), 381-394.

Out-of-the-loop performance, as a result of automation of functions, results in the loss of manual skills and the loss of awareness of the state and processes of the system. Providing adequate feedback under automation to keep the operator informed, but not overloaded, is a formidable challenge for system designers. With this background, an experiment was conducted in which a cognitive task was automated via a simulated expert system. The independent variable was the level of control, including manual, decision support, consensual artificial intelligence (AI), monitored AI, and full automation of a simulated decision task related to driving. Dependent variables included decision time, decision selection, decision confidence, workload, and SA. Overall, the results suggest the importance in maintaining SA in the out-of-the-loop performance problem. It seems that the loss of SA is a result of (a) problems with vigilance and complacency, (b) lack of active information processing, and (c) reduced or altered feedback on system state. Based on the context of this particular study, it is most likely that loss of SA is most attributed to the difference between active and passive information processing. The general trend exhibited in the responses was that full automation produced more problems than did partial automation, which in turn produced more problems than the manual condition.

15. Federal Aviation Administration (2012). *Integration of Unmanned Aircraft Systems into the National Airspace System: Concept of Operations*. Retrieved from http://www.suasnews.com/wp-content/uploads/2012/10/FAA-UAS-Conops-Version-2-0-1.pdf

The document presents a vision for the integration of UAS into the NAS from an air traffic management perspective. Currently, only aircraft that obtain a Certificate of Waiver of Authorization (COA) or special airworthiness certificate are allowed access to the NAS. Furthermore, ATC is required to segregate UAVs from manned aircraft, which is sufficient for today's demand, but may not be in the future. One of the greatest challenges to UAS integration is the use of instruments to replace the vision of a pilot, as vision is fundamental to the conduct of flight operations. Also, UAVs have unique flight profiles, for which ATC policies, procedures, and training do not currently exist. Many airports do not have the infrastructure to support UAS departures and arrivals. Regarding data and communication links, their loss currently occurs too frequently for NAS integration. Going forward, the FAA has identified three key perspectives regarding UAS-NAS integration: accommodation, integration, and evolution. The document concludes by detailing nine operational UAS scenarios, such as flight planning, surface operations, and various missions in all classes of airspace.

16. Federal Aviation Admininstration (2013). *Integration of Civil Unmanned Aircraft Systems (UAS) in the National Airspace System (NAS) Roadmap*. Retrieved from http://www.faa.gov/uas/media/uas_roadmap_2013.pdf

This document was written by the FAA to illustrate the significant undertaking it is to build the basis for the NAS to transition from UAS accommodation to UAS integration. The roadmap is organized into three perspectives: accommodation, integration, and evolution. Specific technology challenges include sense and avoid capability and control and communications system performance requirements. Regarding UAS accommodation, the FAA's near-term focus will be on safely allowing for expanded operation of UAS in the NAS. In the mid-term, emphasis will shift from accommodation to integration, characterized by the implementation of civil standards for UAS operators and new or revised operational rules, together with policy guidance and procedures. Finally, regarding evolution, the long-term focus for UAS operations is the continued refinement and updating of regulation, policy, and standards, with the end goal of streamlined processes for the continued integration of UAS into the NAS.

17. Fern, L., Kenny, C. A., Shively, R. J., & Johnson, W. (2012). *UAS integration into the NAS: an examination of baseline compliance in the current airspace system.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

There remains a need to provide UAS pilots with necessary traffic information in an integrated and intuitive fashion to meet see-and-avoid requirements comparable to manned aircraft. With this in mind, the objectives of the experiment were to examine baseline conditions for UAS operating in the NAS alongside manned aircraft, and to examine the effects of introducing a basic traffic display into a UAS GCS. 12 certified pilots participated in an experiment in which they flew a highway patrol police mission in high-density Los Angeles airspace. Two cockpit situation display (CSD) conditions (absent, present) and two traffic density conditions (low, high) were crossed and administered to all pilots. The CSD displayed aircraft trajectories and colored intruders based on their altitude relative to ownship. During the mission, participants were required to reroute the UAS when issued new instructions from their commander and communicate with ATC to negotiate flight plan changes and respond to vectoring and altitude change instructions. Dependent measures collected included minimum horizontal and vertical distance between ownship and intruders, the number of losses of separation (LOS), subjective NASA-TLX workload ratings, and Likert-scale SA ratings. There was no effect of CSD condition on average minimum horizontal and vertical distances, nor a significant effect on the number of losses of separation. There also was no significant effect on workload in using the CSD, but workload was significantly higher regarding ATC interactions when the CSD was not present in the GCS. SA was rated higher with the CSD present in five of the six SA queries presented to pilots after experiment completion. The results suggest that most of the separation assurance responsibility falls on ATC (indicated by the lack of significant performance or workload effects), but the addition of the CSD did significantly aid in pilot SA without increasing workload. The presence of a traffic display will likely have a larger effect when the pilot is tasked with maintaining self-separation.

18. Fern, L., Rorie, R. C., Pack, J. S., Shively, R. J., & Draper, M. H. (2015). *An evaluation of Detect and Avoid (DAA) displays for unmanned aircraft systems: The effect of information level and display location on pilot performance.* Paper presented at the Proceedings of 15th AIAA Aviation Technology, Integration, and Operations Conference.

A human-in-the-loop simulation study was conducted on pilot use of a detect-and-avoid (DAA) display for avoiding traffic and completing a mission. Pilots flew two routes during which they were responsible for navigating an aircraft and responding to a variety of scripted health and status tasks. Two independent variables were examined, including a full within-subject crossing of information level (basic, advanced) and display location (standalone, integrated). The advanced display condition contained all of the information elements contained in the basic display condition plus an additional collision avoidance alerting level, a depiction of predicted CPA, a 0.8-nm "well clear" threshold ring, a vertical situation display, a single maneuver recommendation, and trial/vector planning tools. The integrated display condition saw the DAA features integrated directly into the moving-map display, while the standalone condition saw the DAA features presented in their own dedicated display. Responses included pilot RTs at eight discrete and operationally-relevant stages of pilot self-separation. Results revealed that generally, the advanced displays resulted in shorter RTs, but there were no statistical differences regarding the display location.

19. Fern, L., & Shively, J. (2011). *Designing airspace displays to support rapid immersion for UAS handoffs.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Under current UAS operations, operators are required to review previous communications conducted in a dedicated chat room with multiple users to determine the status of a UAS before taking control of the vehicle via a handoff. Interviews with operators and other SMEs revealed the difficulty in searching and absorbing all of this information in this manner. Therefore, the research in this document assesses the effectiveness of four different display formats in conveying relevant information during a transfer of control. The four formats included a baseline display (requiring participants to read through chat history to assess the state of the UAS), a text display (presenting textual information about the state of the UAS), a graphics display (providing a map containing relevant information about UAS status), and a map display (relevant information overlaid on the tactical situation display). Participants were given control mid-flight and were asked to perform the following tasks, in order of priority: (1) monitor airspace and clearance information; (2) monitor aircraft flight and health systems; and (3) conduct surveillance on a ground convoy in the UAS sensor window. Dependent variables included the time to determine airspace and aircraft system status, the time spent on each of the three mission tasks, and SA via probe response accuracy. SA was measured for the airspace status, aircraft systems, and mission. Finally, subjective ratings of ease of use, workload, and information availability were collected via Likert scale ratings. Results revealed that time to determine airspace status was significantly shorter in the text and graphics display than in the baseline chat history display, but no significant differences among the display types on time spent on each mission. Similarly, the baseline display yielded significantly lower SA than the three remaining displays, with no statistical differences among the text, graphics, and map displays. Similar trends were exhibited for subjective ratings of usefulness, ease of use, and workload. The map overlay display was ranked as the most preferred display, followed by the graphics display, the text display, and the baseline display.

20. Friedman-Berg, F., Rein, J., & Racine, N. (2014). *Minimum visual information requirements for detect and avoid in unmanned aircraft systems.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

A human-in-the-loop study was conducted with the objective of identifying minimum information requirements for UAS operators in a detect-and-avoid task. Four levels of information were manipulated (labeled Position, Direction, Prediction, and Rate) as well as four levels of UAS operator separation authority. Dependent variables included subjective questionnaire responses, number of near mid-air collisions, minimum separation from an intruder, intruder tau values, and the visual attention distribution across the displays. In general, objective responses and effectiveness ratings plateaued at the Prediction level of information, which provided projection of future aircraft states and conflict alerting, without requiring significantly more workload or attention. This suggests that the minimum intruder information required by UAS operators is: aircraft ID, range, bearing, relative altitude, range, absolute altitude, heading chevron, heading, climb/descend arrow, conflict alert color coding, and vector lines.

21. Hardman, N., Colombi, J., Jacques, D., Hill, R. R., & Miller, J. E. (2009). An evaluation of collision avoidance technologies using empirical function allocation. *International Journal of Applied Aviation Studies, 9*(2), 133-154.

Function allocation is an important issue in the development of new systems, but there exist few quantitative methods for assessment. With this in mind, the work proposes a method to assist designers in making human-computer function allocation decisions, and provide an example of their method applied to traffic collision avoidance for UAS. The six-step process includes identification of tasks, decomposition of tasks by information processing stages, quantifying human and machine performance for each task, and comparing alternatives. The method is demonstrated via a UAS collision avoidance application and, taking into account potential link delays and scan pattern frequencies, reveal that humans may not be capable of manual performing the DAA task, suggesting high LOAs.

22. Hobbs, A., & Lyall, B. (2015). *Human Factors Guidelines for Unmanned Aircraft System Ground Control Stations*. Retrieved from http://humanfactors.arc.nasa.gov/publications/GCS_HF%20_Prelim_Guidelines_Hobbs_Lyall.pdf

This is a working document on guidelines for UAS GCSs for civil aircraft operating beyond line-of-sight, updated in September 2015. The guidelines are focused on issues unique to UAS, as there already exists myriad of literature on human factors in manned aircraft. The guidelines presented in the document have been developed on the basis of data from simulations, accident and incident analyses, and literature on UAS human factors considerations.

23. Hobbs, A., & Shively, R. J. (2013). Human Factors Guidelines for UAS in the National Airspace System. *Proceedings of Association for Unmanned Vehicle Systems International (AUVSI)*, *12*, 15.

Human-system integration of UAS into the NAS is presented, with a focus on how NASA is working with community partners to develop a set of recommendations for human factors guidelines for GCSs. Many UAS display requirements are the same as manned pilot requirements, such as airspeed, attitude, and performance of onboard systems. Information unique to UAS requirements includes strength of the command link, information from on-board cameras, and status information on the GCS itself. Furthermore, UAS are increasingly controlled with point-and-click interfaces. UAS pilot tasks can be categorized as "aviate", "navigate", "communicate", and "manage". In general, a waterfall approach to GCS guidelines development needs to be taken, from the existing CFR to existing UAS requirements to general human factors standards, and resulting in the development of new guidelines.

24. Jenkins, D. P. (2012). Using cognitive work analysis to describe the role of UAVs in military operations. *Theoretical Issues in Ergonomics Science*, *13*(3), 335-357. doi:10.1080/1463922X.2010.506560

A task analysis and resulting function allocation strategy is presented for the application of military UASs. A work domain analysis is performed first, resulting in a hierarchy of goals, functions, and objects. This hierarchy is subsequently used in an activity analysis to map the functions from the work domain analysis to various situations encountered by a military UAS, including the development of a decision ladder and the various tasks and information requirements associated with each decision. The third step was a social organization and cooperation analysis, which yielded assignment of LOAs to all relevant functions. The paper concludes by offering a set of broad recommendations for UAS human-machine interface design.

25. Joint Planning and Development Office (2013). *Unmanned aircraft systems (UAS) comprehensive plan–a report on the nation's UAS path forward*. Retrieved from http://www.faa.gov/about/office_org/headquarters_offices/agi/reports/media/uas_comprehensive_plan.pdf

The document presents the overall goals and objectives regarding the integration of UAS into the NAS based on 12 existing technical reports, concepts of operation, roadmaps, etc. written by various agencies, such as the Federal Aviation Administration, Department of Defense, National Aeronautics and Space Administration, etc. Six goals and eight national objectives were defined based on the existing documents, including one goal to "define, determine, and establish acceptable levels of automation for UAS in the NAS" and one objective to "develop and integrate UAS enabling technologies within the NAS infrastructure to support appropriate levels of automation".

26. Kenny, C., Shively, R. J., & Jordan, K. (2014). *Unmanned Aircraft System (UAS) Delegation of Separation in NextGen Airspace*. Retrieved from http://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20140017682.pdf

The experiment assessed the feasibility of UAS performing delegated separation in the NAS, manipulating two levels of delegation and two levels of traffic display information level. Levels of traffic information level included a display with basic intruder information, such as call sign, altitude, airspeed, and color-coded relative altitude, and a more advanced display containing visual and auditory conflict alerts. Participants were required to fly a CO_2 emissions monitoring task through Los Angeles airspace while communicating with confederate ATC and confederate intruder pilots. The level of information did not statistically affect the number of losses of separation, in-flight workload probes, post-flight NASA-TLX ratings, or post-flight subjective SA ratings. However, the conflict detection alerting functionality significantly increased in-flight SA probe accuracy compared to the basic display. Finally, usability ratings revealed pilot preference for the conflict detection functionality over the basic display.

27. Kenny, C., & Fern, L. (2012). Varying levels of automation on UAS operator responses to traffic resolution advisories in civil airspace. *Advances in human aspects of aviation*, 279-288.

The experiment investigated the effects of varying LOAs on UAS operator performance and workload while responding to conflict resolution instructions provided by TCAS II during a UAS mission in high-density airspace. Participants flew a signal intelligence mission with four LOAs for responding to TCAS II RAs. The four LOAs tested were manual operation, knobs, management by exception, and full automation. Dependent measures included RT to RAs, response rate, compliance rate, pre-emptive response rate, and NASA-TLX workload ratings. Management by exception led to smaller RT and higher compliance rate than the manual and knobs conditions (full automation was not included in analyses since all RAs were responded to immediately). Operators also made significantly more preemptive responses in the manual condition compared to the knobs and management by exception conditions. Overall TLX ratings were not significantly affected by the LOAs, but there were significant differences in the physical and temporal subdimensions. Overall, the results indicate that RT and compliance rates for unmanned aircraft operating at lower LOAs could be unacceptable in the NAS environment. Furthermore, operators remarked that the manual and knobs conditions took "too long" to perform edits required for collision avoidance, so they began to preemptively edit before an RA was given (i.e., adapted to the automation conditions).

28. Kirlik, A. (1993). Modeling strategic behavior in human-automation interaction: Why an "aid" can (and should) go unused. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 35*(2), 221-242.

First, an experiment was conducted utilizing a multitasking light helicopter flying task, in which participants had the freedom to switch between manual control and autopilot modes while dealing with the demands of a secondary, text-editing task. The authors suspected that the participants would utilize the autopilot when completing the secondary task, but found that the secondary task had no effect on the use of the autopilot. These results motivated a Markov Decision Process (MDP) model to identify features of aid design and task context that influence the strategy the operators developed. The MDP model reflected states associated with adaptable automation and rewards and costs associated with transitioning between states. The goal of the MDP model was to determine the optimal policy for using the autopilot. A sensitivity analysis of the model parameters revealed that the optimal strategy occurred only in areas that are not representative of the context in which participants performed the task. This suggests that the combination of the hypothesized factors determined operator willingness to engage the automation.

29. Lam, T. M., Mulder, M., & van Paassen, M. M. (2007). Haptic Interface for UAV Collision Avoidance. *The International Journal of Aviation Psychology*, *17*(2), 167-195. doi:10.1080/10508410701328649

GCSs typically rely on the presentation of information visually, so the addition of more visual information leads to more scanning and more interpretation of information, both demanding cognitive processes. With this in mind, this study considers the use of force feedback to allow the tele-operator to perceive information of the environment in the manual tele-operation of a control-augmented UAS helicopter. Three LOAs of conflict detection and alerting were tested: no haptic feedback; haptic feedback with a conventional artificial force field (GPF), and haptic feedback using a novel artificial force field (PRF) developed by the authors. The haptic feedback on the joystick was activated when the helicopter came too close in proximity to an obstacle (e.g., a wall), forcing the joystick away from the surface. Participants flew 6 subtasks with the 3 LOAs, with 5 total replications. Dependent measures included the number of collisions, elapsed time for each subtask, average UAV speed, UAV speed standard deviation, minimum and maximum UAV speed, minimum distance to an obstacle, time spent within a critical distance to an obstacle, standard deviation of the total hand moment on the stick (control activity), subjective workload rating, and subjective perceptions of the LOA. The results showed that haptic feedback significantly reduced the number of collisions, increased control activity, increased the distance to obstacles, decreased time inside the critical distance, decreased average speed, and increased speed deviations. GPF led to larger elapsed times than both PRF and the no-feedback condition and workload, measured using the NASA-TLX, was highest for GPF, followed by PRF, then by the no-feedback condition. Overall, the study revealed the potential positive effects of haptic feedback, and the balance between the automation and the workload imposed on the operators.

30. Lee, S. M., & Mueller, E. R. (2013). A Systems-Based Approach to Functional Decomposition and Allocation for Developing UAS Operational Concepts. doi:10.2514/6.2013-4241

The purpose of the research was to describe a systems-based approach employed to develop a range of concepts intended to explore a range of allocations of UAS separation assurance functions. An approach using a hierarchical decomposition method and a functional allocation method was taken to identify and allocate required separation assurance functions. The authors conducted a hierarchical functional analysis for separation assurance of UAS operating in the enroute and transition airspace through rigorous literature surveys, site visits, and interviews with subject-matter experts (SMEs). A Hierarchical Task Analysis (HTA) was then used to identify required separation assurance functions from top-level concept goals and a function allocation framework was proposed for different types and LOA. The goal of the study was not to make recommendations for separation assurance function allocation; rather, it was to show the systems-engineering methodology for developing a set of function allocations. Three methods are introduced to measure the effectiveness of the function allocations: stability analysis, workflow analysis, and task load analysis. Further work will need to be completed to assess the most effective allocations, through simulations, SME input, etc.

31. McCarley, J. S., & Wickens, C. D. (2005). *Human factors implications of UAVs in the national airspace*: University of Illinois at Urbana-Champaign, Aviation Human Factors Division.

The work examines the existing research literature on the human factors of unmanned flight, and delineates issues for future research to address, divided into four categories: (1) automation; (2) perceptual and cognitive aspects of pilot interface; (3) air traffic management procedures; and (4) crew qualifications. Regarding automation issues, current UASs vary in the degree to which enroute flight control is automated, ranging from stick-and-throttle control to fully automated UASs flying pre-programmed routes. It may not be possible to issue a blanket recommendation for all UAS aircraft in civilian airspace; likely, the best solution regarding automation will be dependent on the characteristics of the flight operation. Another issue concerns standardization across UASs; certain commonalities should be established across all interfaces. Overall, the paper gives a list of future directions of research regarding human factors issues inherent with UAS operation.

32. Miller, C. A., & Parasuraman, R. (2007). Designing for flexible interaction between humans and automation: Delegation interfaces for supervisory control. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *49*(1), 57-75.

The authors provide a brief review of the work done in human-automation interaction, and propose that the human should remain in charge of all automation, deciding how much automation to use (termed adaptable automation). Too little automation can result in excessive workload for the operator, while too much automation can induce complacency or skill degradation. Therefore, the authors suggest that a mixture of human and automation involvement is desirable compared to fully manual or fully automated systems. Merging the ideas of adaptable and flexible automation, the paper closes with a prototype interface named “The Playbook” which facilitates operator assignment of LOAs to tasks at his/her convenience during a task.

33. Monk, K., Shively, R. J., Fern, L., & Rorie, R. C. (2015). *Effects of Display Location and Information Level on UAS Pilot Assessments of a Detect and Avoid System.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Details novel results from the experiment presented in Fern et al. (2015). Two independent variables were manipulated for the detect-and-avoid interface, including basic vs. advanced level of information and standalone vs. integrated location in the GCS. The dependent variables measured in the study focused on subjective preferences of the pilots on training sufficiency, initial alert response, conflict assessment and avoidance, ease of use, clutter, performance degradation, alerting logic, display location, and information sufficiency. Results revealed pilot preference for the integrated display, particularly when the advanced set of information was available, despite the fact that the ratings revealed advanced information to contribute to display clutter. They also rated the integrated display as more conducive to safe operations. Overall, the advanced tools seemed to be more intuitive when integrated with the GCS command-and-control interface.

34. Mouloua, M., Gilson, R., & Hancock, P. (2003). Human-centered design of unmanned aerial vehicles. *Ergonomics in Design: The Quarterly of Human Factors Applications, 11*(1), 6-11.

There are many advantages to the use of UASs, such as the ability to operate “fearlessly” in battle and in areas contaminated by biotoxins or radiation. However, remote operation of a vehicle provides many human factors challenges to the design of interfaces and training of personnel. Regarding the automation of UAS functions, there are three major possible levels of UAV flight control: full manual control, supervisory control, and full automation. A task analysis revealed many issues related to UAS operation, of which the most important were described. These included data-link delays, control design, cognitive workload limitations, SA and assessment, detecting targets, and designing for training and teaming. Regarding cognitive workload limitations, the authors highlight the importance of appropriate formatting and editing of data to facilitate efficient perception and interpretation of information. Furthermore, automation of target detection functions can provide a major benefit to UAS operators engaged in target search and recognition missions. Overall, the authors recommend a hybrid manual/automated control for military UASs, but a general recommendation like this may not be appropriate for UAS flight in civilian airspace.

35. Nehme, C. E., Crandall, J. W., & Cummings, M. (2007). *An operator function taxonomy for unmanned aerial vehicle missions.* Paper presented at the 12th international command and control research and technology symposium.

Summary:

The authors present a taxonomy of UAS missions, including those currently performed and those that could possibly be performed in the future. The first level of the taxonomy contains seven general groups of tasks, including intelligence/reconnaissance, drones, transport, extraction, insertion, communication, and surveillance. Each task at the lowest level of the taxonomy consists of three phases: mission planning, mission management, and mission re-planning. The authors report the functional and information requirements for each task. The authors further identify the operator functions that exist in at least half of the missions, including monitoring the health and status of UAS, notifying relevant stakeholders, optimal position supervision, path planning supervision, and resource allocation/scheduling.

36. Onnasch, L., Wickens, C. D., Li, H., & Manzey, D. (2014). Human Performance Consequences of Stages and Levels of Automation: An Integrated Meta-Analysis. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 0018720813501549.

The authors first review the literature on levels of automation and the four stages of information processing. At the end of their review, they propose three postulates regarding automation: (1) a higher level of automation constitutes "more automation"; (2) a later stage of information processing constitutes "more automation"; and (3) a combination of a higher level of automation and a greater number of stages at which automation is implemented constitutes "more automation". Related to this, the authors define *Degree of Automation* (DOA) as the combination of level of automation and stage of information processing. Finally, the authors present the results of a meta-analysis on the effects of DOA on "metavariables" of routine primary task performance, return-to-manual primary task performance, workload, and SA. In particular, the work sought to empirically identify a tradeoff between workload and SA at increasing DOAs, as well as the conventional wisdom that increased DOA makes system failures more catastrophic. In general, both expectations were supported. Further analysis revealed negative consequences of automation are most likely when DOA moves from information analysis automation to action selection automation, both in routine conditions and upon experiencing a system failure.

37. Pack, J. S., Draper, M. H., Darrah, S. J., Squire, M. P., & Cooks, A. (2015). *Exploring Performance Differences between UAS Sense-and-Avoid Displays.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

A human-in-the-loop experiment was conducted in which two independent variables were manipulated: sense-and-avoid (SAA) display configuration and presence/absence of displayed weather. Five SAA display types were tested, manipulating the level of current-state information, projected future information, and automated maneuver assistance. Results revealed that there were very few differences in the objective performance measures (reliance on maneuver automation, RT to alert, and number of collision avoidance alerts) as a function of the display types and the weather conditions. The banding display yielded RT ~3 sec faster than the remaining displays, but did not reach statistical significance. However, subjective feedback revealed that the UAS pilots generally preferred the banding display over the remaining four display types.

38. Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 39*(2), 230-253.

The paper examines the human performance aspects of automation, analyzing factors influencing human use of automation. Automation does not supplant human activity, it changes the nature of the work that humans do, often in unintended and unanticipated ways. Therefore, it is necessary to investigate how operators and designers make decisions to use, misuse, disuse, and abuse automation. Regarding use of automation, the literature suggests that automation decisions are based on a complex interaction of many factors and are subject to strongly divergent individual considerations (e.g., reliability, trust, workload, confidence, etc.). Regarding misuse of automation, system designers should be aware of the potential for operators to use automation when they probably should not, to be susceptible to decision biases caused by overreliance on automation, to fail to monitor the automation as closely as they should, and to invest more trust in the automation than it may merit. Regarding disuse of automation, designers of alerting systems must take into account both the decision threshold and the base rate of the hazardous condition in order for operators to trust and utilize the system; a high false alarm rate will likely lead to disuse of automation. Finally, regarding abuse of automation, failure to take a human-centered approach to function allocation can reduce or even nullify the economic or other benefits automation can provide.

39. Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 30*(3), 286-297.

The authors present a model of LOAs at the four stages of human information processing: information acquisition, information analysis, decision and action selection, and action implementation. At each of these stages, there is a spectrum of automation ranging from fully manual to fully automated. Following this was a flow chart on how designers should allocate the various LOAs to the human information processing stages, featuring an iterative approach, with effectiveness measured via mental workload, SA, complacency, and skill degradation. Finally, a series of recommendations for choosing the appropriate LOA at each stage of processing is presented.

40. Prinet, J. C., Terhune, A., & Sarter, N. B. (2012). *Supporting Dynamic Re-Planning In Multiple Uav Control: A Comparison of 3 Levels of Automation.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Participants supervised 9 UAVs in a target detection task that intermittently required re-planning, while simultaneously responding to occasional chat messages. Three path-planning LOAs were manipulated, and participants performed three missions, each containing nine re-planning tasks. Workload was also manipulated within each mission through the number of tasks/events that occurred within three seconds of one another. Dependent variables included target detection time and accuracy, RT to the re-planning notification, time required to complete the re-planning, and re-planning "score," which measured the quality of the re-planned route. The automation condition yielded the fastest completion time, highest re-planning score, and highest number of UAVs shot down by enemy weapons, followed by the intermediate LOA, and the manual LOA across all dependent variables. There was no significant difference in target detection accuracy between the automated and intermediate LOAs, but both yielded significantly higher accuracy than the manual condition. Subjective perceptions revealed that full automation was most helpful of the three levels during periods of high workload.

41. Rash, C. E., LeDuc, P. A., & Manning, S. D. (2006). Human factors in US military unmanned aerial vehicle accidents *Human Factors of Remotely Operated Vehicles* (Vol. 7, pp. 117-131).

Two approaches to military UAS accident characterization were taken; one using the Human Factors Analysis and Classification System (HFACS) and the other using the Department of Army Pamphlet 385-40 (DA PAM). HFACS uses four main categories for incident/accident characterization (unsafe acts, unsafe preconditions, unsafe supervision, and organizational influences) while DA PAM uses five main categories (individual failure, leader failure, training failure, support failure, and standards failure). In general, the taxonomies revealed that human error in UAS operations occurs frequently during training and most often in the difficult phases of flight, such as takeoffs and landings.

42. Rorie, R. C., & Fern, L. (2014). *UAS measured response the effect of GCS control mode interfaces on pilot ability to comply with ATC clearances.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

A critical issue for UAS operations in the NAS is how pilots transition from “on-the-loop” operations (e.g., supervising autopilot) to “in-the-loop” operations (e.g., hands on stick and throttle) quickly and effectively. Related to this, the study examined the effect of different command and control interfaces on UAS pilot ability to get “in-the-loop” to respond to ATC clearances. Three control modes were presented to pilots, including waypoint editing, autopilot, and manual stick-and-throttle. 15 UAS pilots flew a pre-filed flight plan, including a stepped grid pattern, and were required to immediately comply with ATC requests. Responses included the various “measured response” times (RTs) associated with the stages of completing a conflict resolution maneuver. In general, the waypoint editing method yielded the longest RTs. For the overall time to receive, plan, and complete the maneuver, the manual stick-and-throttle interface led to the shortest RT, followed by the autopilot mode, followed by the waypoint editing mode. In general, the auto-pilot and manual modes allowed participants to generate successful maneuvers on their first attempt, unlike the waypoint-editing mode, contributing to the longer RTs associated with the waypoint editing mode.

43. Rorie, R. C., & Fern, L. (2015). *The impact of integrated maneuver guidance information on UAS pilots performing the Detect and Avoid task.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Summary:

The requisite amount of information that should be provided to a UAS pilot for maintaining self-separation through the detect-and-avoid (DAA) system has not yet been determined. Prior research found that pilot DAA performance was enhanced when using an Advanced DAA system, which included a suite of DAA features. This research was an extension of that research which aimed to determine which features included in the suite of advanced features yielded the greatest DAA performance benefit. The four DAA display combinations included Advanced Information, Advanced Information + Vector Planner Tools, Advanced Information + Auto-Resolutions, and Advanced Information + Vector Planner Tools + Auto-Resolutions, all used via a point-and-click interface. Participants were asked to fly a pre-planned route while complying with ATC clearances and monitoring secondary chat and health and status tasks. Dependent variables included “measured response” times (RTs), the elapsed times of the varying stages of avoiding a conflict. In general, displays containing the vector planning tools yielded longer RTs than displays containing Auto-resolutions. Using the vector planning tools, pilots were responsible for determining a successful maneuver, which took much longer than simply accepting a recommended resolution maneuver.

44. Rorie, R. C., Fern, L., & Shively, J. (2016). The Impact of Suggestive Maneuver Guidance on UAS Pilot Performing the Detect and Avoid Function *AIAA Infotech@ Aerospace* (pp. 1002).

In a continued attempt to develop minimum operational performance standards for UAS detect-and-avoid system, the study presented pilots with four different display types, one with no maneuver guidance and three with different forms of suggestive maneuver guidance (including alert bands and vector planning tools). Pilots were asked to fly two routes while responding to a variety of scripted health and status tasks in a chat client while also completing electronic checklists in response to aircraft system malfunctions. Pilots were encouraged to minimize the magnitude of any deviations off of the planned route and return to route as soon as possible. Dependent measures included "measured response" times (RT), which measured the time required to complete different phases of the resolution maneuver tasks, and maneuver statistics, such as maneuver type, maneuver size, and proportion of encounters with multiple uploads. In general, the two banding conditions (no fly and omni) resulted in the smallest RTs, followed by vector planning tools, with the information-only condition yielding the longest RTs. The results also revealed that across all display conditions, pilots overwhelmingly preferred lateral maneuvers to vertical and combination maneuvers. Finally, the three suggestive maneuver guidance conditions led to smaller deviations from the planned trajectory and fewer encounters with multiple maneuver uploads than the information-only condition. This suggests that an "information only" level of information that lacks maneuver guidance is unlikely to be sufficient to support acceptable pilot performance on the DAA task of remaining well clear. The authors suggest that suggestive maneuver guidance be made a minimum requirement for future DAA systems, via continuous presentation of guidance information rather than requiring pilot interaction with display features or tools.

45. Rudnick, G., Clauß, S., & Schulte, A. (2014). *Flight testing of agent supervisory control on heterogeneous unmanned aerial system platforms.* Paper presented at the 2014 IEEE/AIAA 33rd Digital Avionics Systems Conference (DASC), 5-9 Oct. 2014, Piscataway, NJ, USA.

This article reports the execution of two flights using a cognitive architecture facilitating supervisory control of the vehicles. A participant was asked to supervise the flight for a fixed-wing UAV and a multirotor aircraft from a common GCS. The cognitive architecture used was capable of planning and decision-making based on explicit a-priori knowledge implemented at design time and situational knowledge gathered during mission execution. The human operator has authority over the system and delegates tasks to the automation. In general, the human-automation team was successful in performing two similar surveillance and target detection tasks.

46. Ruff, H. A., Draper, M. H., Lu, L. G., Poole, M. R., & Repperger, D. W. (2000). *Haptic feedback as a supplemental method of alerting UAV operators to the onset of turbulence.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

A human-in-the-loop study was conducted to assess the effectiveness of haptic feedback on alerting pilots of turbulence in a UAS landing task. Four independent variables were manipulated, including haptic feedback (accompanied by a visual alert), turbulence strength, turbulence direction, and proximity of the turbulence to the runway. Subjective dependent measures were collected, including subjective SA ratings, self-assessed landing performance ratings, and perception of the direction and severity of the turbulence in each trial. Overall SA ratings were higher for the haptic condition than for the non-haptic conditions, and an interaction effect revealed greater facilitation of the haptic condition on SA when the aircraft was further from the runway at turbulence onset. Participants rated landing difficulty to increase under the haptic condition compared to the non-haptic condition, but only three out of the five participants preferred the haptic feedback condition. Overall, the inclusion of the haptic/visual alerting yielded mixed results, which the authors attribute to the strong forces associated with the joystick, potentially limiting operators in their control of the aircraft.

47. Ruff, H. A., Narayanan, S., & Draper, M. H. (2002). Human interaction with levels of automation and decision-aid fidelity in the supervisory control of multiple simulated unmanned air vehicles. *Presence: Teleoperators and virtual environments, 11*(4), 335-351.

An empirical evaluation of three variables was conducted in a simulated target acquisition task, including LOA (manual, management-by-consent, management-by-exception), decision aid fidelity (95% accuracy, 100% accuracy), and number of UAVs controlled (one, two, four). Dependent variables included performance measures of mission efficiency (defined as the total number of targets destroyed divided by total number of missiles fired), correct rejection rate of incorrect decision aids, event management, subjective workload ratings, and subjective SA ratings. LOA had a significant effect on mission efficiency such that management-by-consent led to higher efficiency than manual control or management-by-exception. Furthermore, management-by-consent yielded higher performance across all of the mission performance measures, followed by management-by-exception, followed by the manual condition. Post-experiment workload ratings revealed the manual condition to cause significantly higher workload than the management-by-exception condition, followed by the management-by-consent condition in the 95% reliability condition. A significant main effect of LOA on SA revealed management-by-consent yielded higher self-rated SA than both the manual and management-by-exception conditions. Overall, management-by-consent maintains human-in-the-loop system functionality while reducing responsibility for functions that the operator does poorly.

48. Santiago, C., & Mueller, E. R. (2015). Pilot Evaluation of a UAS Detect-and-Avoid System's Effectiveness in Remaining Well Clear. Paper presented at the Eleventh UAS/Europe Air Traffic Management Research and Development Seminar (ATM2015).

Two related experiments are presented on various parameters of UAS detect-and-avoid (DAA) systems. In experiment 1, three independent variables are manipulated, including DAA display location (stand-alone vs. integrated), information level (basic vs. advanced), and timing of alerts relative to closest point of approach (CPA; 80 sec vs. 110 sec). Experiment 2, building on the results of experiment 1, tested the decomposition of the features in the advanced display in experiment 1, yielding four display configurations (basic information, trial planner tool, maneuver recommendation, and trial planner + maneuver recommendation). Dependent variables included the number of losses-of-well-clear, separation at CPA, and pilot RTs to DAA alerts. In general, the integrated display condition yielded fewer losses of well clear and the advanced integrated display yielded fewer losses of well clear than the other three configurations in experiment 1. In experiment 2, fewer losses of well clear occurred with the displays containing the maneuver recommendation functionality, but ANOVAs revealed a lack of statistical differences among the displays.

49. Sheridan, T. B., & Parasuraman, R. (2005). Human-automation interaction. *Reviews of human factors and ergonomics, 1*(1), 89-129.

A review of seminal research and challenges in the area of human-automation interaction is presented. The review is broken up into sections on taxonomies and qualitative models, automation-related incidents and accidents, human performance research, quantitative models, and adaptive automation.

50. Shively, R. J., Hobbs, A., Lyall, B., & Rorie, C. (2015). Human Performance Considerations for Remotely Piloted Aircraft Systems (RPAS).

The document provides a summary and recommendations for human factors considerations for successful integration of Remotely Piloted Aircraft Systems (RPAS) into civil airspace. The document covers six areas of RPAS human factors considerations, including personnel licensing, RPA operations, airworthiness, command and control, DAA, and ATM integration.

51. Shively, R. J., Neiswander, G. M., & Fern, L. (2011). *Manned-unmanned teaming: Delegation control of Unmanned Aerial Systems (UAS).* Paper presented at the 67th American Helicopter Society International Annual Forum 2011, May 3, 2011 - May 5, 2011, Virginia Beach, VA.

The experiment tested three levels of UAS control on low-level terrain flight missions requiring operators to perform a primary task of target identification and a secondary task of responding to communication queries. The UAS was operated by a simulated helicopter co-pilot while conducting the mission. The three control levels included no UAV, a "manual" condition requiring use of a waypoint editing interface, and a "playbook" condition in which the UAS operator chose the "play" necessary for task completion. Results revealed little difference among the control levels in terms of correct identification of threat vs. non-threat vehicles, but route planning took longer in the manual condition than in the playbook condition, NASA-TLX ratings were higher for the manual condition than the remaining two conditions, and pilots ranked the playbook interface as the most desirable condition.

52. Stanard, T., Bearden, G., & Rothwell, C. (2013). *A cognitive task analysis to elicit preliminary requirements for an automated UAV verification planning system.* Paper presented at the 57th Human Factors and Ergonomics Society Annual Meeting - 2013, HFES 2013, September 30, 2013 - October 4, 2013, San Diego, CA.

SMEs were given a monitoring task requiring the use of four UAVs to surveil a “VIP vehicle” traveling from an origin to a destination. A think-aloud verbal protocol was used as experimenters presented different scenarios to the SMEs and recorded their responses. At the end of the “table top exercise”, participants gave feedback on automation strategies that would have benefited their performance in the exercise. Although the task included a four-UAV task, the recommendations provided by the experts are relevant for single-UAV operation.

53. Tvaryanas, A. P. (2006). *Human factors considerations in migration of unmanned aircraft system (UAS) operator control*. Retrieved from http://www.wpafb.af.mil/shared/media/document/AFD-090121-046.pdf

There is very little work investigating the human factors issues associated with transfer of UAS control, so the current work reported the results of a literature review on the topic. Control can be transferred between operators in a single control station, between control stations, or among members of a crew. There are many human factors issues that can be mitigated by using multiple operators/teams to control a UAS, including reducing operator fatigue and associated vigilance decrements, facilitating enhanced operator functional specialization, and decreasing workload by distributing tasks across multiple crew members. The major disadvantage is degraded SA for the operator/crew receiving control responsibilities. Overall, the ability to transfer control of UAS operation and tasks is promising, but more work needs to be done to assess the potential human factors implications.

54. Van Dijk, H., & De Reus, A. (2010). *Automation and multiple ua control.* Paper presented at the 27th Congress of the International Council of the Aeronautical Sciences 2010, ICAS 2010, September 19, 2010 - September 24, 2010, Nice, France.

A human-in-the-loop experiment was conducted in which teams of two operators (an air vehicle operator (AVO) and a payload operator) operated one, two, or four aircraft in a mission requiring the operators to detect, count, and report certain ground targets of interest. Two LOAs were manipulated on the alerting of two system failures: high engine temperature or low fuel. Results revealed that the LOA had no significant effect on AVO workload, SA, detection of system failures, or flying performance. The lack of significance is likely due to the simplicity of the task; the AVO was not required to communicate with ATC or monitor for potential collisions with other aircraft or terrain. Furthermore, the taskload was distributed across two crewmembers, leaving ample attentional resources available for monitoring system status.

55. Wickens, C. D., & Dixon, S. (2002). *Workload demands of remotely piloted vehicle supervision and control: (1) single vehicle performance*. Retrieved from http://www.dtic.mil/dtic/tr/fulltext/u2/a496813.pdf

The objective of the experiment was to assess how well pilots fly a remotely-piloted vehicle unaided, with auditory offloading, and with automation offloading of some of its tasks. Participants were required to perform three tasks: a tracking/navigation task, a target-search task, and a system failure monitoring task. Three LOAs were assessed, including a baseline condition with no automation requiring flight via joystick, an auditory condition in which instructions and alerts were presented aurally rather than visually, and an automation condition in which participants entered the coordinates of the next waypoint for the aircraft to fly to via autopilot. In general, the auditory alerting condition aided detection of system failures (accuracy and RT) during normal, enroute flight, but had no effect on the responses during the higher workload periods during which participants were performing image inspection tasks. The automation condition was successful in freeing operator resources to perform the secondary tasks, such as target search and system health monitoring, resulting in higher detection rates in those tasks compared to the baseline condition.

56. Wickens, C. D., Dixon, S., & Chang, D. (2003). *Using interference models to predict performance in a multiple-task UAV environment-2 UAVs*. Retrieved from

Operating an UAS is a visually demanding task. The research investigates the potential benefits of offloading visual tasks to automation (via an autopilot functionality) and to the auditory modality (via aural alerts of system health parameters). This research was a continuation of a previous experiment (Wickens and Dixon, 2002), in which pilots operated one- and two-UAV scenarios searching for command targets (CTs), targets of opportunity (TOOs), and monitoring for system failures (SF). This study differed from the prior study in that performance-based incentives were offered to participants to increase motivation. Pilots performed the tasks under three conditions-baseline, auditory offload of CT instructions and SF alerts, and flight path tracking automation offload. Under the single-UAV condition, the automation offload generally improved TOO monitoring and SF detection, while the auditory offload assisted SF detection, but had not effect of the TOO task. There was no evidence of cognitive tunneling in this experiment (unlike the previous experiment), an effect that may be attributable to the performance-based incentives offered to participants.

57. Wickens, C. D., Li, H., Santamaria, A., Sebok, A., & Sarter, N. B. (2010). *Stages and levels of automation: An integrated meta-analysis.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

The authors posit that, in addition to a higher level of automation, a later stage of information processing reflects a higher degree of automation. To test this, a structured literature review and meta-analysis was conducted, which also tested the tradeoff between performance in normal operations and failure condition as a function of degree of automation. The results 17 studies were aggregated into three levels of significance by p-value: $p<0.05$, $0.05<p<0.10$, and $p>0.10$. The dependent variables analyzed were performance (which differed by study), workload, and SA. The results revealed that as more automation benefits performance, it also reduces workload, and that increasing benefits with higher automation are accompanied by increasing costs for imperfectly reliable automation. In general, the theory that higher automation yields worst performance in failure conditions is not well supported.

58. Williams, K. W. (2004). *A summary of unmanned aircraft accident/incident data: Human factors implications*. Retrieved from http://www.dtic.mil/get-tr-doc/pdf?AD=ADA460102

The report reviewed currently-available information on military UAS accidents to determine to what extent human error contributed to those accidents and to identify specific human factors involved in the accidents. Separate results were reported for the five primary UASs in service: Hunter (Army), Shadow (Army), Pioneer (Navy), Predator (Air Force), and Global Hawk (Air Force). Overall, electrical and mechanical reliability play as much or more of a role in accidents as human error. Human factors issues were attributed to accidents between 21% (Shadow) and 67% (Predator) of the time, suggesting that they are very much dependent on the particular systems being flown and the user interface being employed. A majority of the accidents occurred in the takeoff and landing portions of the flight, during which the EP was in control of the aircraft. In other words, systems for which the takeoff and landing portions were automated resulted in lower human-factors-related accidents.

59. Williams, K. W. (2006). *Human factors implications of unmanned aircraft accidents: Flight-control problems*. Retrieved from http://ntl.bts.gov/lib/34000/34000/34063/GetTRDoc.pdf

Based on the results of a prior accident analysis, the work assessed three categories associated with accidents across UASs, including recommendations on mitigation strategies. The three categories included the use of an EP, transfer of control during flight, and automation of flight control. EPs can have issues mapping the direction of the controller joysticks to the direction that the aircraft turns since the EP's perspective of the vehicle is not "behind the wheel." Regarding transfer of control, a common theme across mishaps is the lack of awareness of system settings on the part of the receiving crew. Finally, many mishaps resulting from control automation exhibit evidence that developers were not able to predict all possible contingencies, leading to situations in which the automation performed as designed, but not as anticipated.

60. Williams, K. W. (2008). *Documentation of sensory information in the operation of unmanned aircraft systems*. Retrieved from http://www.faa.gov/data_research/research/med_humanfacs/oamtechreports/2000s/media/200823.pdf

Accident analyses suggest that between 15% and 25% of UAS accidents are due at least in part to a lack of sensory information. Therefore, it is very important to design UAS control stations to account for the lack of sensory feedback compared to pilots of manned aircraft. This document reviews the literature on human sensory capabilities, then provides an explicit comparison of the sensory information available to UAS operators compared to manned aircraft. The review concludes by making suggestions on alert design and utilization of non-visual channels for delivering information to UAS operators.

61. Williams, K. W. (2012). *An Investigation of Sensory Information, Levels of Automation, and Piloting Experience on Unmanned Aircraft Pilot Performance*. Retrieved from http://www.faa.gov/data_research/research/med_humanfacs/oamtechreports/2010s/media/201204.pdf

The experiment aims to provide empirical support for the need to have multiple sources of sensory information available to pilots to enhance their ability to diagnose and respond to system failures. Further, the experiment assesses whether it is necessary for UAS operators to have prior manned flight experience. LOA in UAS control was also an experimental manipulation (vector control vs. waypoint control). Participants were required to respond to heading and engine failures while flying a route. Dependent variables included response rate to failures, flight technical error, traffic monitoring, awareness of relative position, and NASA-TLX workload. The addition of auditory engine-failure alerts facilitated prompt responses, but many pilots responded to the heading control failures before the alerting was triggered. The LOA had little effect on any of the dependent variables, potentially due to the relatively simple nature of the task or fact that both vector control and waypoint entry are relatively high levels of control automation.