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Interaction of Automation Visibility and Information Quality in Flight Deck Information Automation View Document

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***Abstract*— An empirical study evaluated key human factors issues related to automation visibility and information quality, based on a refined definition of information automation. Next Generation Air Transportation System operational concepts will dramatically affect the types and amount of information available on flight decks. Information automation systems collect, process, and present information to support pilot tasks and awareness. The definition of flight deck information automation was refined to differentiate it from other types of automation. Pilots interacted with an example information automation system to investigate the premise that automation visibility will have an impact on the ability of pilots to detect problems resulting from poor information quality. Poor information quality appeared to be difficult for pilots to detect, even when presented with high automation visibility. Pilots tended to over-trust automation, so when reporting high workload and information was missing, they chose the top plan suggested by the automation even though it was not the best. Trust in automation was reduced by low information quality, but compensated for by increased automation visibility. Added information to help pilots understand information automation state and outputs, given a level of information quality, should be balanced against potential increases in pilot workload due to the time and attention needed to process the extra information.**

***Index Terms*— Automation Visibility, Human Factors, Information Automation, Information Quality,**

I. Introduction

Economic factors and rapidly emerging technology have continued to be the driving forces behind automation system development, resulting in a shift of human roles and responsibilities from an active operator to essentially that of monitor, error handler, and automation manager [4], [5], roles for which it is known that humans are not well suited [6], [7]. Conveying the right information at the right time to human operators and accepting input from them in a user-friendly manner is critical for safe operations. As manufacturers develop applications to accommodate the demand for new capabilities, they must consider the implications of human factors issues in the design of the interactions between pilots and automation.

In the aviation domain, modern flight decks utilize sophisticated automation systems. Beyond current operations, there is considerable research and development in new automation, procedures, and concepts to safely and efficiently handle an increasing demand for air travel. Next Generation Air Transportation System (NextGen) will utilize satellite-based navigation and interconnected database systems to guide and track air traffic more precisely than previously feasible [1]. This transformation will result in new automation to take advantage of the likely increase in the amount of available information [2]. NextGen operational concepts and technologies will dramatically affect both the types and amount of information available on flight decks [3].

The literature on human factors aspects of flight deck “automation” typically makes little distinction among different types of automation (e.g. [8], [9]). However, there may be different human factors issues depending on the type of automation being considered. Much of the automation currently being developed pertains to information support rather than aircraft control. Information automation is defined as automation devoted to the management and presentation of relevant information to flightcrew members [11]. The Performance-based Operations Aviation Rulemaking Committee/Commercial Aviation Safety Team Flight Deck Automation Working Group has recommended that a stronger definition of information automation is needed, as well as defining associated terms [11]. Based on definitions of Billings [12] and Parasuraman, Sheridan, & Wickens [13], we developed a two-dimensional description of flight deck

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information automation [14] that considered what is being managed (aircraft, systems, or information), and the stage of information processing involved.

Certain human factors issues and pilot errors which might be prevalent in interacting with information automation may be minimal for other types of automation. The primary goals of information automation systems are to promote situation awareness and assist in decision making tasks for the flightcrew, both of which are specifically related to human information processing and cognition. Conversely, direct control of the aircraft and its subsystems are more heavily dependent on psychomotor skills and strategic mission planning. As such, there are likely unique human factors issues that must be considered when designing the interaction behavior of information automation systems that differ from other types of automation.

More automation will push flight crews into becoming more of mission, task, and information managers, to the point where management knowledge and skills are as important as traditional flying skills. Some of these "cognitive" skills could include "information triage" – categorizing and prioritizing information quickly and efficiently, searching and accessing information, and validating information quality. To investigate the role automation support has in these cognitive skills, an empirical study evaluated human factors issues related to the interaction between Automation Visibility and Information Quality. Information Quality is the degree to which the information is fit for use and can affect whether the information can be reliably used by the automation or the pilot [15]. Automation Visibility is the degree to which information is available to assist the user in understanding the system's behavior [4]. This includes the means by which the system provides information to allow the pilot to understand what sources of information the system uses as input, what reasoning it uses, and how it generates outputs.

II. Flight Deck Information Automation Framework

A. Definition and Framework

Billings [12] distinguished information automation from control automation (which directly impacts the motion of the vehicle) and management automation (which impacts efficient mission completion). While control automation is clearly distinct from information and management automation, further details to distinguish these latter two are necessary.

Information automation is applicable to many different domains [17]. Landry [2] suggests that information automation is distinguished from other types of automation as it is intended to provide information to support reasoning by the operator (as opposed to supporting rule-based or skill-based behavior). Abbott et al. [11] define information automation as "automation devoted to the management and presentation of relevant information to flightcrew members." We adopt this definition here, but for clarity, we decomposed information automation into more specific categories, presented in Fig. 1.

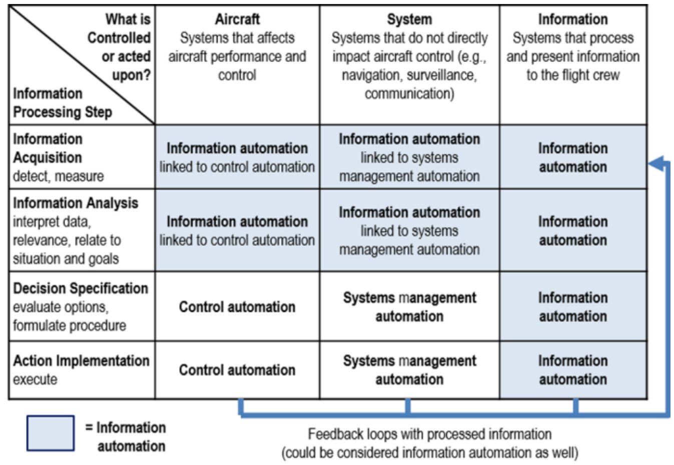

Fig. 1. A two-dimensional framework for describing information automation.

The horizontal dimension of the framework shows "What is controlled or acted upon?" The column headings represent parameters similar to the aviation automation types identified by Billings [16] and reflect what the automation is controlling: the aircraft, the mission, or information. Requirements for integrity and redundancy levels will be different depending on whether the automation is managing or acting upon controls, planning, or information, as will the detectability of errors. The rows show what stage of information processing is being performed by the automation. We apply the four-stage information processing model described by Parasuraman et al. [13]: (1) Information Acquisition, (2) Information Analysis, (3) Decision Selection, and (4) Action.

In the framework presented here, the definition of information automation is expanded to include not only the first two stages of processing, but also the final two stages if what is being controlled is information itself. For instance, decision automation may or may not be classified as information automation. Automation in the Decision-Selection/Information cell that evaluates display options to decide the best way to convey information to the pilot would be information automation. More specifically, the framework can be used to define different areas considered to be information automation:

- Early information processing stages (information acquisition, information analysis) linked to control and management automation
- All information processing stages for automation where information is the primary commodity being controlled, processed and presented
- Feedback loops present information on statuses and states for control and systems automation (while these loops might not strictly be considered information automation, similar human factors issues likely apply).

Automation that manages or acts upon information (4th column in Fig. 1) and support the decision selection (4^{th} row in Fig. 1) stage of processing is the principal focus of this study. Decision selection tasks require "cognitive" skills including categorizing and prioritizing information quickly and efficiently, searching and accessing information, and validating information quality[19].

The design of automated decision aids should include considerations of how much information is made available to the operator about the rationale, criteria, uncertainty, and determining factors used in forming the aid's judgments and actions [18]. The uncertainty considered by the automation, and how that uncertainty is communicated to the human, also impact operator decision making [20] and performance [21]. As automation takes over these types of tasks, the amount of visibility into the reasoning of the automation, as well as the quality of information used by the automation are important as humans monitor and assess the outputs of the automation. To investigate the role automation support has in these cognitive skills, the study in this paper focused on Information Quality and Automation Visibility, described below.

B. Information Quality

Previous research in information quality originated in database administration and management of information systems ([22], [23], [24], [25], [26], [15]). Wang and Strong [15] identified four properties of high quality data: 1) intrinsically good, 2) contextually appropriate for the task, 3) clearly represented, and 4) accessible to the data consumer. They further identified 15 dimensions within the four properties to capture the usefulness of information as a product, or commodity, to the consumers who seek it (see Table I). The evaluation in this paper focused on dimensions of completeness and appropriate amounts of data of the information used by the automation to make its recommendations.

TABLE I
CATEGORIES AND DIMENSIONS OF INFORMATION QUALITY [15]

Intrinsically Good	**Contextually Appropriate for Task**	**Clearly Represented**	**Accessible to Data Consumer**
Believability Accuracy Objectivity Reputation	Value-added Relevancy Timeliness ***Completeness*** ***Appropriate amount of data***	Interpretability Ease of Understanding Representational consistency Concise representation	Accessibility Access security

The dimensions of information quality include many aspects of information systems directly relevant to pilots as consumers of information automation output. For example, automatic de-cluttering of a display aims to provide only the most relevant and timely information for a given situation [27]. Information quality can be degraded by [22]: erroneous system input; incomplete, uncertain, or probabilistic input; poor assumptions or unaccounted for factors [28]; flawed or imprecise processing (e.g. due to a limited or constrained model) [29]; conflicting inputs from a variety of data sources; inaccurate or unreliable outputs [30]; and delayed or untimely information.

C. Information Automation Visibility

Automation Visibility refers to the ability of an automation system to provide adequate feedback to the user about its current state, what information was used, and how the information was processed [32], [33]. This characteristic has also been referred to as transparency, opacity, or observability (e.g. [36], [37], [38], [39], [40], [41]). Various related definitions include the support an operator's comprehension about the intent, performance, and the reasoning process [37]. Others include the concept of "broadening" where a system can reveal multiple solutions to enable the joint human-automation system to explore a broader set of candidate solutions [42].

In order for automation to be visible, feedback must provide a view into the automation state in a manner which can be properly interpreted by the operator [41] and allows the operator to predict its behavior [43]. This includes information about input sources and how the system is generating outputs. High automation visibility enhances predictability by fostering the development of an accurate mental model and enables the flightcrew to verify outputs. Poor automation visibility has been shown to result in a loss of situation awareness and an increase in workload [44], [45]. However, the appropriate amount and timing of "explanatory" information must be carefully evaluated because too much information presented at an inappropriate time (e.g., during time-critical tasks) adds workload and head down time [46], [47]. Broadening the number of options considered, for instance, could increase the amount of information to process, thus increasing operator workload unless there is a concomitant offloading of complex calculations [37]. Studies have shown that inadequate automation visibility contributes to information automation human factors issues including: poor predictability of behavior [48], [43]; hard-to-detect input or processing errors [44], [4]; difficult-to-assess Information Quality and verify outputs [48], [4]; and inadequate, inappropriately timed, or inappropriate amount of system feedback (e.g., modes) [10], [11].

In addition, human-automation interaction is complicated by a feedback loop between the automation's judgments and the human's information seeking, cue utilization, and judgment policy [18]. Studies have shown that if the algorithms used by the automation are highly complex, and are dissimilar from the human's strategies or not understood by the human, the automation's outputs were ignored [49], [50]. On the other hand, overly simplistic strategies were disregarded as nuisances [51]. The type and level of information about automation reasoning and behavior has a strong effect on the human's trust, and results in under- or over-reliance on automation [39], [54]. Increased automation visibility may actually decrease trust, if the greater visibility reveals that the information is less reliable [37]. Therefore, increased visibility may result in more appropriately calibrated trust [39]. Furthermore, the amount and type of information about the underlying logic greatly influences how pilots use that awareness when forming strategies and responses. For instance, Pritchett [52] demonstrated that pilot non-conformance increased when a traffic display that provided position-based measures of collusion hazards, but the underlying alerting system's logic was based on convergence rate.

III. Method

An experiment explored the interplay between automation visibility and information quality in the context of a decision aiding automation. Automation visibility was operationalized as the amount of information that automation provides about the reasoning behind its recommendation, and Information quality is operationalized as the completeness of the information about which the automation reasons.

A. Hypothesis

Automated systems can suffer from brittleness when the system model does not account for all possible scenarios. For a decision support system, presenting recommendations compromised by system brittleness can strongly degrade decision-making [53]. Increasing automation visibility may help to prevent automation surprises [34], increase the ability of human operators to understand what the system is doing [31][35], and critique the information quality of inputs to the automation [19]. However, the increased information will require more time and resources to process and validate automation reasoning [19]. The evaluation is based on a premise that automation visibility will have an impact on the ability of pilots to detect problems resulting from poor information quality. Specifically, there were three hypotheses tested in the study.

H1) Increased information quality will result in better primary task performance compared to lower information quality.

H2) Increased automation visibility will result in increased primary task performance, increased confidence in decisions, and increased trust in automation, increased automation awareness, but at a cost of higher workload and higher attention allocation to the display.

H3) Increased automation visibility will result in increased ability for pilots to compensate for poor information quality in the automation to maintain overall primary task performance (i.e., the difference in primary task performance between the low and high information quality conditions will be greater when automation visibility is low than when the visibility is high).

B. Participants

Twelve air transport pilots from a cross section of regional and major airlines were recruited. All were male. Five were Captains and seven were First Officers. All had flown glass cockpits. Average age was 34.2 (range 24-56) with about 7,000 flight hours (range: 2,000-14,000). Participants rated their familiarity with glass cockpits as 4.9 of a 5-point scale (*SD* = 0.3), trust in automation as 3.85 (*SD* = 0.58), and level of authority in diversion decision making as 4.08 (*SD* = 1.08).

C. Experiment Task: Diversion Decision-Making

1) Background

To test the hypotheses, a Diversion Aid was developed as an example of automation that controls information (Fig. 1, 4th column) to support the participants in decision specification (Fig 1, 4th row). Historically, diversion decisions have been a collaborative effort between the pilot and airline dispatchers. The Diversion Aid is envisioned for a future where pilots take advantage of the increased information available in NextGen to take primary responsibility for diversion decisions. While the primary goal is safety, diversion decisions have significant impact on downstream airline operations, including the schedules for aircraft, crew, maintenance, and passengers. Experienced dispatchers will consider the operational implications of diversions [55]. There are typically several different diversion plans possible that will maintain safe flight and landing profiles, but the plans differ widely in their impact on airline operations, profit, crew and staff convenience, and customer satisfaction. In future operations, it is anticipated that pilots will be expected to take a more active role in considering these aspects of diversion decisions.

2) Diversion Aid

The Diversion Aid integrates multiple information sources on the current state of flight, aircraft, maintenance, crew, and passenger schedules to display the implications of diversion decisions to pilots. The goal is for pilots to integrate the goals and priorities of interested airline operations stakeholders into the decision making process. This was based on a previously developed system [55] that uses a set of policy statements and cost values developed after interviews with airline dispatchers, pilots, and various stakeholders (see Table II). The policy statements represent the operational priorities of all stakeholders affected by diversion decisions and assess the overall "goodness" of a diversion plan. For a particular plan, each policy violation was associated with cost points. Diverting a flight with an unaccompanied minor costs 10 points, while delaying a flight greater than 15 minutes costs 8 points. The goal of selecting a diversion option that minimizes the total cost incurred: the lower the cost, the better the plan.

TABLE II
Policy Statements and Their Corresponding Cost Values.

Policy Statement	Cost
Do not exceed crew duty limits (nine hours flying time per day)	10
Do not divert a flight with an unaccompanied minor	10
Do not divert a flight with an arriving international passenger to an airport that does not have passport control	10
Do not divert passengers connecting to an international flight	8
Do not delay flights greater than 15 minutes	8
Do not divert to an airport that has its maximum capacity of aircraft	8
Do not cause crew to miss next flight assignment	5
Do not cause passengers to fail to reach destination	3

3) Displays

The Diversion Aid presented the original scheduled flight plan, followed by up to three diversion plans, ranked based on minimizing policy violations. Fig. 2 is an example of high visibility, where the original plan is shown at the top for comparison to the three suggested plans below. Each plan depicts the flight schedule of the aircraft (airport codes between the horizontal bars). If there is text within a bar, this indicates that there is a policy violation on the flight, with the number of points above it. Depiction of each individual policy violation allows pilots to understand how the Diversion Aid ranked one plan ahead of another. The code (e.g. Px, Int) described the category of the violation, and there is a key at the bottom of the display for quick reference. Pilots can also access a help tab to see the policy violations and their weights (Table II). A second row of flights may be displayed for a plan if a dependency between this aircraft and others exists; for example, if a flight crew was going to transfer to a different aircraft. Yellow triangles indicate scheduled maintenance. The total Decision cost is presented next to the select button. Option 1 of Fig. 2 suggests diverting the current (first) flight of the day from DEN to APA, and then continuing on to ABQ (thereby recovering the scheduled third stop). This incurs 11 points of policy violations for the passengers who were expecting to deplane at APA, and 8 points for international passengers who will now miss their connections. The second and third leg of this plan each both incur 8 points, due to passenger impacts, for a total plan penalty of 27 points. Medium visibility would be the same display but without the policy violations and points displayed. Low visibility would only depict one alternate option.

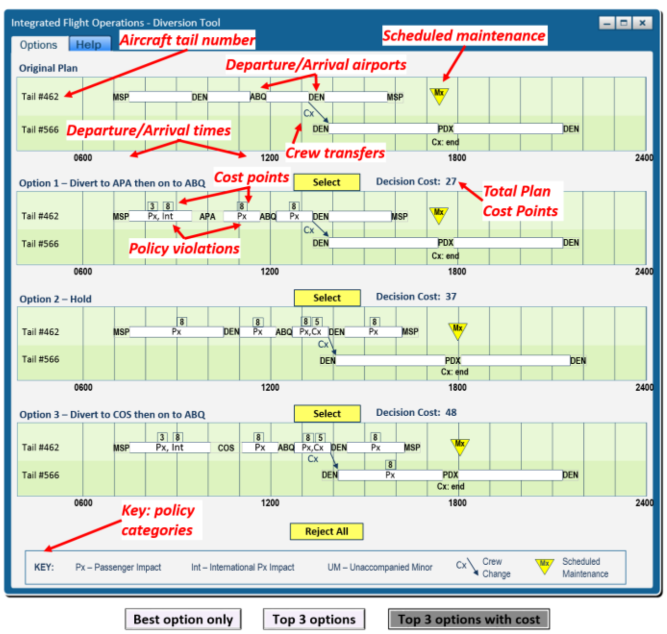

Fig. 2. Diversion Aid with high Automation Visibility, displaying the top three ranked options with policy violations.

D. *Tasks/Scenarios*

Participants performed two tasks: 1) select/reject a diversion plan with the help of the Diversion Aid, and 2) report traffic as it appeared in an out-the-window display. In every trial, participants knew they would be diverted, but did not know when in the scenario they would be instructed to divert.

1) *Diversion Plan Selection*

Participants were told that the Diversion Aid had already considered all aspects of flight safety, such as remaining fuel and runway lengths at suggested diversion airports. As such, they were to focus on consequences of diversion options from an airline operations perspective. Participants acted as the pilot monitoring. In the pre-flight briefing, the confederate pilot reviewed the day's schedule, weather, and pre-planned diversion airport. These briefings contained both relevant and irrelevant information specific to the diversion task, in order to provide the information that might be needed to make a correct decision without explicitly stating that the information would be required. For example, the participant may be briefed that their flight has an unaccompanied minor on board. The information in the briefings changed with each flight. Participants were informed that the Diversion Aid may not always have the most current or correct information. Participants were also told that the briefings had the most accurate and up-to-date information and they, as pilots, had the final authority in the diversion decision. After reviewing the Diversion Aid's recommended plan(s), the participant decided whether to accept one of the plans or to reject its recommendation(s) if he or she felt a better plan could be devised. The participant did not need to create a different plan. A Help menu displayed the policy set and was always available.

2) *Reporting Traffic*

A secondary task of reporting traffic in a simulated out-the-window view was given to measure workload as a secondary task during the diversion selection task. Traffic appeared out the window in random locations at random times and did not move. Every five seconds, the probability of traffic being displayed was 60% (a set point determined during pre-experimental testing). If traffic appeared, it remained in view until the participant pressed a button, or five seconds had elapsed.

E. *Independent Variables*

Table III summarizes the two independent variables: Information Quality and Automation Visibility.

TABLE III
INDEPENDENT VARIABLES FOR THE EVALUATION.

Independent Variable	Levels	Description
Information Quality	Low	Some relevant information was not included in the calculation of total diversion decision cost
	High	All relevant information was included in the calculation of total diversion decision cost
Automation Visibility	Low	Best option only
	Medium	Rank-ordered list of the three best options
	High	Rank-ordered list of the three best options with the costs shown

In the high Information Quality condition, the correct selection was always the top option on the display. In the low Information Quality condition, the correct selection was not the top selection, because the automation was missing information that resulted in incomplete scoring of the options. However, participants were given knowledge of this "missing" information during the pre-flight briefing. Therefore, in the low Information Quality conditions, the automation's highest ranked plan was not actually the best plan – participants were expected to recognize that a different plan was better once they included the missing information (known to them) into to their assessment. Selecting the top recommendation of the aid would be the correct (best) selection 0% of the time in the low Information Quality condition and 100% in the High Information Quality condition.

Automation Visibility was defined as the amount of information that the automation reveals about its reasoning. This includes the number of options considered, the rules used to assess these options, the consequences of each option, the benefits and costs associated with each option, and the stakeholders that are impacted by the options. There were three levels of Automation Visibility: 1) low visibility, where a single best option was presented; 2) medium visibility, where a ranked list of the top three options is presented; and 3) high visibility, where a ranked list of the top three options with the cost values were shown (see Fig. 2). In all cases the automation makes a recommendation to the pilot. In the low visibility condition only this recommendation is shown. The medium visibility condition broadens the exposure to the automation's reasoning by presenting not only the recommendation but two other plans considered but not recommended. Finally, the high visibility condition shows three plans plus the policy violations that drove the scoring. The independent variable Automation Visibility manipulated two types of information: presentation of the number of options, and the costs associated with each option. Other types of information were kept constant: the rules used to assess these options (policy definitions), the consequences of each option (depiction of the downstream schedules), the stakeholders impacted by the options (categories of stakeholders affected by policy violations).

The difference between the medium and high Automation Visibility conditions is the display the costs associated with each option, and is a manipulation the underlying logic of the automation [36][38][40]. The difference between the low and medium Automation Visibility conditions can be considered as a manipulation of the level of decision automation (the third stage in the framework) in the tradition of Parasuraman et al [13] and Sheridan & Verplank [56]. The low Automaton Visibility has a high level of decision automation (offer only one alternative), and the medium Automaton Visibility is a lower level of decision automation (offer multiple options) [56]. Thus the three levels of Automation visibility are a nested combination of presenting two types of information: 1) level of decision automaton (number of options presented) and 2) the display of automation reasoning, in which visibility is nested within low level automation. The design is summarized in Table IV. Overall, the low visibility condition contains the least amount of information, and the high visibility combination contains the most.

TABLE IV
DEFINITIONS OF THE THREE LEVELS OF AUTOMATION VISIBILITY.

Automaton Visibility Levels:	Low	Medium	high
Information presented	1 option No logic	3 options No logic	3 options Logic
Level of automation reasoning	Low	Low	High
Level of decision automation	High	Low	Low

A third independent variable was originally included: Display Modality (text, graphic), with identical information content. However, since there were no statistically significant differences between the text and graphic displays, the data were collapsed over this variable.

F. Dependent Variables

See Table V for a summary of the dependent variables in the study. Decision Performance was measured by the time to make a diversion decision and the correctness of the decision. In all Automation Visibility levels, the participant could select a plan or select a "Reject All" option. Time to make a decision was the elapsed time from the start of the diversion task (i.e. when the participant was informed of the need for a diversion) until participants made their diversion plan selection. Workload while selecting a diversion plan was measured subjectively via the NASA-TLX questionnaire [57]. Traffic detection performance can be considered an objective measure of workload. Attention Allocation was estimated by collecting head-tracking data (InterSense® InertiaCube2) and calculating the percentage of time the participant spent looking at the Diversion Aid while selecting a plan. Confidence in their decision, Automation Awareness, and Trust in the Aid's recommendation were measured via a Likert scale question administered after each trial. The five-point scale was labeled with numbers 1 through 5 to underscore the interval character of the scale. The Automation Awareness question asked participants to provide their level of understanding of how the Diversion Aid arrived at its recommendations. In the post-experiment questionnaire participants were asked to describe their decision-making strategies in the different Automation Visibility conditions in an open-ended question.

TABLE V
DEPENDENT VARIABLES FOR THE EVALUATION.

Dependent Variable	Metric	Unit	Frequency of Collection
Decision Performance	Selection of best plan	yes/no	once per trial
	Time to make a selection (all responses)	seconds	once per trial
	Time to make a selection (correct responses only)	seconds	once per trial (correct trials only)
Workload	NASA TLX	0 - 10	once per trial
	Ratio of detected traffic vs. all traffic targets presented	%	2x trial - before and during diversion
Attention Allocation	Time spent on primary and secondary displays (app vs. out-the-window)	seconds	once per trial
Confidence	Likert Scale	1 - 5	once per trial
Automation Awareness	Likert Scale	1 - 5	once per trial
Trust	Likert Scale	1 - 5	once per trial
Decision Aid Features	Free Response		Post-experiment

G. Experimental Design and Procedure

The experiment was a 2 (Information Quality: low, high) x 3 (Automation Visibility: low, medium, high) within-subjects design. Participants performed six (counterbalanced) diversion scenarios. The experimental conditions were also counterbalanced. Participants trained with the Diversion Aid, tasks, and post-trial questionnaires, with periodic quizzes to test understanding of the aid's calculations and recommendations. Participants were expected to critically review the Aid's recommendations to select/reject the diversion plans presented. Flight simulation began approximately 10 minutes from top of decent, during which they were responsible for identifying traffic out the window. After 60-90 seconds, the need for a diversion was announced by the confederate and the participant was asked to make a recommendation within five minutes. Pilots were told to make a diversion decision as quickly as they were comfortable that they had made the best decision. After each decision, they filled out the NASA-TLX workload scale and post-trial questionnaire. After all six scenarios, they filled out a post-experiment questionnaire and were debriefed.

H. Data Analysis Plan

A repeated measure analysis of variance (ANOVA) was used for normally distributed data. Non-parametric Wilcoxon tests were used for non-normally distributed Likert rating data. Results are reported as significant for alpha <.05, and marginally significant for alpha <.10 [58]. The abbreviation "ns" is used to denote non-significant results. Tukey post-hoc tests determined significance between pairwise comparisons of normally distributed data groups. Results will present letters above each group; the letters indicate significant (at the .05 level) pairwise differences between groups when they do not share a letter. Cohen's d calculated an effect size and provides a standard measure that expresses the mean difference between two groups in standard deviation units. Cohen's d results are reported as small effects for .20 < d <.50, medium effects for .50 < d <.80, and large effects for d >.80.

IV. Results

A. Decision Performance

Fig. 3 depicts the plan selection results as a function of Information Quality and indicates significant pairwise differences between groups when they do not share a letter. Information Quality introduced a significant ($F(1,11) = 33.0$, p < .001, d = 1.72) increase in the percentage of correct plans chosen from the low Information Quality condition (M = 36.1%, SE = 8.1%) to the high Information Quality condition (M = 86.1%, SE = 5.8%). Automation Visibility ($F(2,22) = 0.31$, p = .73 ns) and the interaction between Automation Visibility and Information Quality ($F(2,22) = 0.65$, p = .53 ns) did not introduce significant differences.

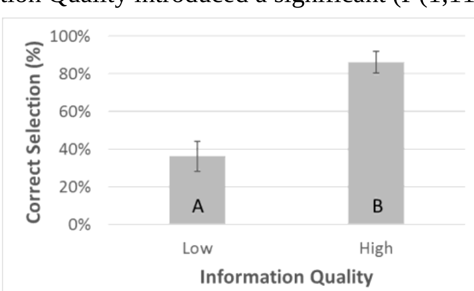

Fig. 3. Correct selection percentage as a function of Information Quality.

Fig. 4 depicts the plan selection time as a function of Automation Visibility. Automation Visibility introduced a significant ($F(2,22) = 3.67$, p = .042) difference in the time to make a selection between conditions, with all trials considered.

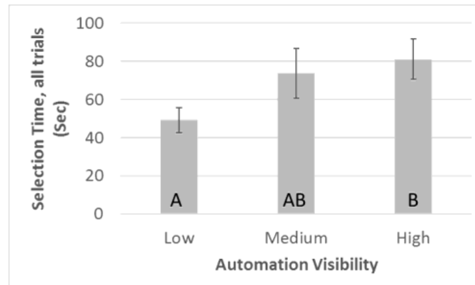

Fig. 4. Plan selection time as a function of Automation Visibility (all trials).

Post hoc analysis indicated that pilots in the low Automation Visibility condition (M = 49.2, SE = 6.6) were significantly (p = 0.043, d = 0.98) faster than pilots in the high Automation Visibility (M = 81.1, SE = 10.8). Information Quality ($F(1,11)$ = 2.87, p = .12 ns) and the interaction between Automation Visibility and Information Quality ($F(2,22) = 0.44$, p = .64 ns) did not introduce significant differences.

When considering only correct response trials, Automation Visibility introduced a significant ($F(2,13.4) = 4.79$, p = .027) difference in the time to make a selection between conditions. Post hoc analysis indicated that pilots in the low Automation Visibility condition (M = 45.0, SE = 8.0) were significantly (p = 0.034, d = 1.15) faster than pilots in the high Automation Visibility (M = 81.9, SE = 14.5). Information Quality introduced a significant ($F(1,12.4) = 8.2$, p = .014) decrease in the selection time from the low Information Quality condition (M = 77.2, SE = 15.8) to the high Information Quality condition (M = 58.6, SE = 8.7). The interaction between Automation Visibility and Information Quality ($F(2,8.4) = 0.13$, p = .88 ns) did not introduce significant differences.

B. Subjective Workload (NASA-TLX)

Of the six subscales of the NASA TLX workload survey, only mental demand and temporal demand showed significant results (see Fig. 5). Automation Visibility introduced a marginally significant ($F(2,22) = 3.41$, p = .051) difference on mental demand between conditions (see Fig. 5 left). Post hoc analysis indicated that pilots in the low Automation Visibility condition (M = 3.2, SE = 0.37) were significantly (p = .047, d = 0.95) lower than pilots in the medium condition (M = 4.6, SE = 0.51). Information Quality ($F(1,11) = 1.18$, p = .30 ns) and the interaction between Automation Visibility and Information Quality ($F(2,22) = 2.32$, p = .12 ns) did not introduce significant differences.

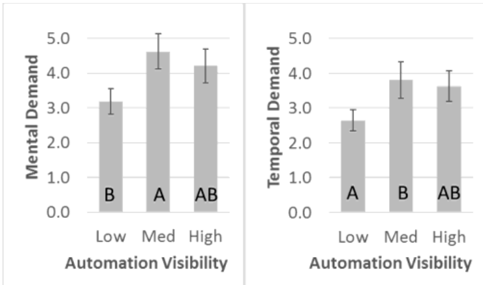

Fig. 5. Mental demand (left) and temporal demand (right).

Automation Visibility introduced a significant (F(2,22) = 4.56, p = 0.022) difference on temporal demand between conditions (see Fig. 5 right). Post hoc analysis indicated that pilots in the low Automation Visibility condition (M = 2.6, SE = 0.31) experience significantly (p = 0.027, d = 0.79) lower temporal demand compared to pilots in the medium level (M = 3.8, SE = 0.53) and marginally significantly (p = 0.068, d = 0.71) lower than pilots in the high Automation Visibility condition (M = 3.6, SE = 0.45). Information Quality (F(1,11) = 0.239, p = .63 ns) and the interaction between Automation Visibility and Information Quality (F(2,22) = 0.118, p = .89 ns) did not introduce significant differences.

C. *Objective Workload: Secondary Task Performance*

Information Quality introduced a marginally significant (F(1,11) = 4.18, p = 0.065, d = 0.57) increase in the percentage of targets detected from the low Information Quality (M = 76.4, SE = 4.8) condition to the high Information Quality (M = 86.7, SE = 3.7) condition (see Fig. 6). Automation Visibility (F(2,22) = 0.74, p = .49 ns) and the interaction between Automation Visibility and Information Quality (F(2,22) = 0.41, p = .66 ns) did not introduce significant differences.

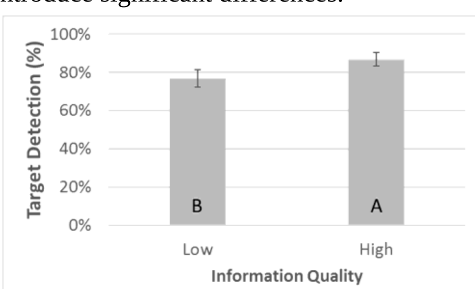

Fig.6. Target detection time as a function of Information Quality.

D. *Attention Allocation*

Automation Visibility introduced a significant (F(2,22) = 9.21, p = 0.001) difference in the amount of time spent on the decision aid between conditions (see Fig. 7).

Post hoc analysis indicated that pilots in the low Automation Visibility condition (M = 31.0%, SE = 3.2%) spent significantly (p = .003, d = 0.93) less time on the aid than pilots in the medium Automation Visibility (M = 41.6%, SE = 3.1%) condition and significantly (p = .002, d = 0.96) less time than the high Automation Visibility (M = 41.3%, SE = 3.1%) conditions. Information Quality (F(1,11) = 2.33, p = .16 ns) and the interaction between Automation Visibility and Information Quality (F(2,22) = 0.48, p = .62 ns) did not introduce significant differences.

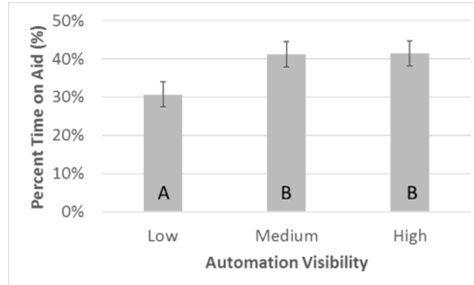

Fig. 7. Percent time spent with head directed toward the Diversion Aid as a function of Automation Visibility.

E. *Confidence*

Information Quality did not introduce significant (Z = 1.59, p = 0.11 ns) differences in the rating of reported confidence. Automation Visibility did not introduce any significant differences between the three levels (see Fig. 8).

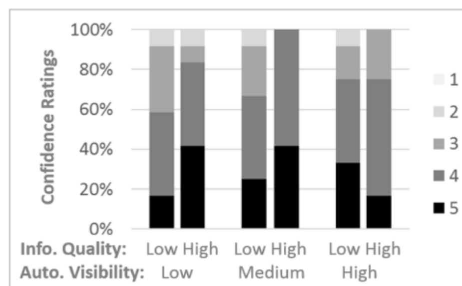

Fig. 8. Confidence rating as a function of Information Quality.

F. *Automation Awareness*

Automation Visibility introduced a significant (Z = 2.38, p = 0.017, d = 1.08) increase in the rating of automation awareness from the medium Automation Visibility condition (M = 3.1, SE = 0.19) than pilots in the high Automation Visibility condition (M = 3.8, SE = 0.16) (see Fig. 9).

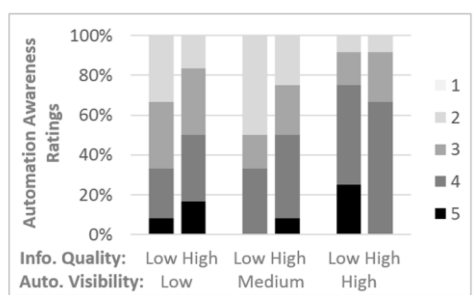

Fig. 9. Automation Awareness as a function of the independent variables.

Pilots in the medium Automation Visibility condition also had a marginally significantly (Z = 1.75, p = 0.08, d = -0.71) lower automation awareness than pilots in the low Automation Visibility condition (M = 3.3, SE = 0.20). Information Quality did not introduce a significant (Z = 0.832, p = 0.41 ns) difference in the automation awareness rating from pilots

G. Trust

Automation Visibility introduced a significant (Z = 2.14, p = .032, d = 0.99) increase in pilot ratings from the low Automation Visibility condition (*M* = 3.4, *SE* = 0.22) than pilots in the high Automation Visibility condition (*M* = 4.0, *SE* = 0.13) (see Fig. 10). Pilots in the medium Automation Visibility condition (*M* = 3.6, *SE* = 0.18) also had a significantly (Z = 2.05, *p* = 0.041, d = 0.87) higher automation awareness than pilots in the low Automation Visibility condition. Information Quality introduced a marginally significant (*Z* = 1382, *p* = 0.068, d = 0.57) increase in the trust rating from pilots in the low Information Quality condition (*M* = 3.5, *SE* = 0.17) to pilots in the high Information Quality condition (*M* = 3.9, *SE* = 0.13).

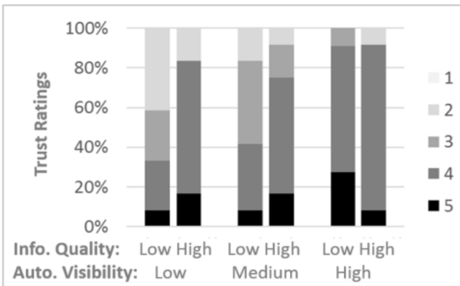

Fig. 10. Trust as a function of the independent variables.

H. Decision Aid Features

The most common positive feedback from participants regarding low and medium Automation Visibility level was its simplicity; however, in both levels, participants wanted more information and reasoning behind the best plan they were being shown (i.e. higher Visibility). The feedback regarding the medium Automation Visibility level was the most varied. Three participants very much liked that three options were offered to them without reasoning information (i.e. costs) to evaluate on their own. Three others commented that they thought this was the worst level to work with because they wanted to either have the best option only (i.e. low Automation Visibility) or the options with the costs (i.e. high Automation Visibility) provided. Generally, participants preferred the inclusion of reasoning information in the high Automation Visibility condition, where three participants commented that they liked having some insight into the financial impact of their diversion decisions. Two participants, however, commented that they did not care at all about those details.

V. Discussion

Hypothesis H1 was partially supported. Diversion plan selection performance was significantly higher when Information Quality was high compared to selection performance when Information Quality was low. In addition, if only the trials where a correct selection was made are considered the time to select was affected by Information Quality. However, the time to make a selection was not affected by Information Quality when all trials were considered.

Hypothesis H2 was partially supported. The level of Automation Visibility did not affect the selection of the best plan, although it did affect decision time (both when considering all trials and when considering only correct trials), with low Automation Visibility leading to the fastest decision time. Since there is less information in the low Automation Visibility level, less attention was required to observe and orient to the task. Between the two higher Automation Visibility levels, the attentional requirements were similar. Although more information is provided at the high level, it was information that was relevant to the decision task and having it readily available may offload cognitive resource requirements, thus balancing the overall attentional requirements.

In low Information Quality, an increase in Automation Visibility from low to high also showed an increase in trust, eventually reaching the trust level seen at high Information Quality, where trust remained constant between Automation Visibility levels. First consider only the low and medium levels of Automation Visibility, where the number of options is different. There is no effect between these levels on automation awareness and trust. However, next consider only the medium and high levels of Automation Visibility, where the number of options is the same. Increased Automation Visibility for low Information Quality increases both automation awareness and trust. In this study, high levels of trust in the automation's recommendations lead to failures to override sub-optimal Diversion Aid recommendations. Confidence did not vary across conditions. This had a negative impact on decision performance when Information Quality was low.

The low level and medium level of Automation Visibility varied in the number of options shown, and can be considered a different level of automation, where the display of a single option (low Automation Visibility) is a higher level of automation. Workload increased from the low to medium level as one would expect as the level of automation decreases. The level of automation was constant between the medium and high levels of Automation Visibility, but the inclusion of cost information in the high Automation Visibility condition reduced the workload needed to assess the three options. One participant commented that he preferred either the low or the high Automation Visibility level, as the medium Automation Visibility level (ranked options without cost) was too much work to interpret: "The single option was superior to rank ordered because a decision made without seeing the reason can just be a suggestion. Three suggestions without the reason behind add more workload. Having the decision cost allowed quicker decision making and a more informed decision." In low information quality, the highest workload was in the medium automation visibility condition, where three plans were presented (hence a lot of information) but the rationale (i.e. policy scores) were not presented, forcing the participant to spend extra effort assessing the quality of each plan. The performance on the secondary task, which can be taken as an indirect measure of workload, was not significantly affected by Automation Visibility. However, the allocation of attention was significantly less for low Automation Visibility and greatest in high Automation Visibility.

Hypothesis H3 was partially supported. Participants had a difficult time detecting when the automation was reasoning over incomplete information, despite the fact that the missing information was known to them. Participants only detected the incomplete information about a third of the time. While previous research in this area (e.g., [45], [59]-[62]) suggests that pilots should be able to compensate for poor automation decisions (in this case driven by poor Information Quality), the results of this study indicate that the type of information presented to increase automation visibility plays an important role. Two factors were used to increase Automation Visibility: broadening the number of options shown, and display of the underlying logic. Increasing the number of options increased the workload, attention required, and decision time with no benefit to automation awareness and trust. Displaying the underlying logic also increased selection time, but it reduced workload. Also, the increased visibility into the underlying logic helped compensate of low formation quality when compared to presenting three options with no logic.

The complexity of the display may also have made it difficult for participants to detect missing information, even when they knew they were looking for it (e.g., the participant who was actively searching to make sure that the unaccompanied minor was in the plan, yet failed to detect that that piece of information was missing). Their generally high trust in the automation caused pilots to spend less time checking for missing information. While they had five minutes to make a decision, the average decision time was within 90 seconds. Even when they intuitively knew something was “not quite right” (as evidenced in the increased time spent making a decision in low Information Quality conditions), they often failed to detect the missing information.

While definitive conclusions are limited by the small number of participants in the study, several areas are presented for further study. Several recommendations are presented in the context of the flight deck human factors considerations described in the FAA Advisory Circular AC 25.1302 [1].

Appropriate levels of information quality could be defined for information automation systems, based on the potential impact of the information on flight safety. This study only looked at a subset of the dimensions of information quality (data that was missing or incomplete). Future work could investigate other dimensions of information quality. Various categories of information quality should be considered, including: intrinsic quality, contextual quality, representational quality, and accessibility. Within these categories are various properties such as accuracy, completeness, and timeliness. AC 25.1302 (p. 28) states that “…information intended for the flightcrew’s use must be provided … at a resolution and precision appropriate to the task.” Precision and resolution are key aspects of quality, but for information automation systems, completeness and timeliness of information can be important.

While increased automation visibility (from medium to high) increased exposure to the underlying reasoning, the additional information presented to the participant was not specifically about the quality of the information it used to reason. Future work could explore the benefits of the automation displaying its own assessment of information quality. This could provide more redundancy in the joint human-automation system, since both the pilot and the automation should ideally be assessing the quality of the information.

VI. Conclusion

The results of the empirical study suggest that pilots may or may not be able to spend extra effort searching for validation information. Providing too much automation visibility information, especially in busy phases of flight, created workload issues. If an information automation system provides choices or alternatives, information on how those choices were determined and their relative merits should be provided. The study did not show a clear preference for a decision aid that showed the best option only versus one that showed multiple options with cost information. However, most participants wanted visibility into how those options, if presented, were determined. They felt it was too much work to determine why the system prioritized the options the way that it did. In comparison to the best option or options with supporting information, presenting options with no supporting information resulted in lower performance, slower performance, higher workload, more attention, and lower automation awareness. But adding information about trade-offs or the automation reasoning for selecting options could also add workload, reinforcing the need to balance visibility with increased information processing requirements.

Other areas of future work include investigation of cognitive skill degradation. As new information systems are introduced into both air transport, business jet, and general aviation markets, increasingly automation is tasked with functions that include calculating, comprehending, reasoning, prediction, and decision making. Much like physical (e.g. flying) skills, it is equally as critical is the retention of the cognitive skills that allow pilots to maintain situation awareness at all times, quickly assess new situations, and make the best decision from the options available to them [63].

VII. Acknowledgments

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