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Impact of Remotely Piloted Aircraft Type on Operations Using the Same Control Station: A Natural Experiment

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The study assessed the impact of RPA heterogeneity on the human performance challenges when operating from a common control station (CCS). All MQ-1 and MQ-9 RPA mishaps from FY 06-11 with associated Human Factors Analysis and Classification System (HFACS) codes were entered into a dataset (N = 88). Logistic regression models were formulated with latent failures as predictors of active failures; RPA type was included as an independent predictor variable and a modifier of predictor variables for latent failures. Also, an exploratory factor analysis was accomplished with RPA type included as a distinct variable. Overall, variation in RPA type did not impart differential demands on the pilot using a CCS.

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1. ABSTRACT

Background: The study objective was to take advantage of a natural experiment and utilize available mishap data to assess the impact of remotely piloted aircraft (RPA) heterogeneity on the human performance challenges when operating an RPA from the same control station—i.e., varying aircraft and holding pilot qualifications and human-machine interface constant.

Methods: All MQ-1 and MQ-9 RPA mishaps reported to the Air Force Safety Center during fiscal years 2006-2011 with associated Human Factors Analysis and Classification System (HFACS) codes were entered into a dataset (N = 88). Logistic regression models were formulated per the HFACS model with latent failures as predictors of active failures; aircraft type was included as an independent predictor variable and a modifier of predictor variables for latent failures. Also, an exploratory factor analysis was used to assess the factorial structure within the dataset; aircraft type was included as a distinct variable.

Results: None of the logistic regression models corresponding to the HFACS active failures included the variable for aircraft, either as an independent term or as an interaction effect with one of the other latent failures. In the factor analysis, the aircraft variable was not associated with any of the variables representing active failures or latent failures at the preconditions tier, the latter including factors addressing attributes of the control station environment and the adverse effects of the control station environment on the crew.

Conclusions: Variation in aircraft type did not impart differential demands on the RPA pilot using a common control station.

2. Introduction

The issue of medical standards for individuals participating solely in remotely piloted aircraft (RPA) operations is a hotly debated topic. Thus, it is noteworthy that surprisingly few studies (1,4) addressing RPA pilot medical standards have been published in the aeromedical literature. As evidence of the disruptive nature of this technology on aerospace medicine, a divergence in logical approaches to formulating medical standards for RPA pilots as compared to traditional pilots has resulted. For aeromedical practitioners, the cardinal disruption results from the fact that the RPA pilot and the aircraft are no longer necessarily co-located. From an occupational medicine perspective, RPAs are, therefore, the engineering control for such traditional aeromedical physical hazards as hypobarics, hypoxia, acceleration, vibration, thermal stress, and those forms of spatial disorientation associated with acceleration. This perspective has led some to argue that controlling one or more RPAs is more akin to air traffic control and thus medical standards for ground-based controller duty are appropriate. Others, such as civil regulators, demonstrate a preference to fit RPA pilots into the existing pilot medical certification categories (e.g., Federal Aviation Administration second class medical standards), which has the advantage of decreasing the burden of new rule making. Lastly, there is the approach that attempts to parse RPA pilot medical standards based on dimensions that are specific to the aircraft, whether in terms of physical (e.g., kinetic energy) or operational (e.g., application categories, airspace usage) attributes (7). The latter considerations underlie the "large versus small" RPA dichotomy and attempts to parse RPA "pilot" versus "operators," respectively.

Which, if any, of these approaches has the best internal consistency and external validity (i.e., generalizability and scalability)? Before answering this question, the aeromedical community must prepare itself for the potentiality that our current challenges addressing RPA operations are only the bow wave of an even larger technological disruption. In the very near future, an RPA pilot will be able to control a spectrum of heterogeneous RPA, either individually or simultaneously from a single control station. Also, emerging RPA system-of-systems architectures are enabling an evolution from the paradigm of "*x* pilots in a control station operating *y* aircraft" to that of "*x* pilots, *y* aircraft (potentially of multiple types), and *z* control stations logged onto a global network." Consequently, an alternative perspective is that, unlike in manned aircraft where the task environment is dictated by aircraft design, the task environment in RPAs is largely dependent on the design of the control station and network and relatively independent of the design of the aircraft.

A significant challenge for the aeromedical research community in addressing the aforementioned issues is the resource requirements to design and execute the needed laboratory experiments to generate scientific evidence. An alternative, compromise approach is to identify and leverage natural experiments, realizing that the quality of evidence may be lower than that obtained in a controlled laboratory study. Fortuitously, such a natural experiment has occurred in the U.S. Air Force (USAF), which uses the same personnel and control station to operate two different RPAs: the MQ-1 Predator and the MQ-9 Reaper (the reader is referred to the RPA-specific USAF factsheets for further description of each aircraft, available at the following URL: http://www.af.mil/information/factsheets/index.asp). Thus it is possible to analyze the effect of changing aircraft type while holding other important system components (i.e., pilot and control station) constant. Complementing this natural experiment is a readily available data source in the form of system mishap data. Mishap data provide a window into patterns of human performance challenges in a system. If aircraft type imparts differential demands on the RPA pilot, it would be expected that aircraft type would then explain some variability in the prevalence of mishap human factors findings. Accordingly, it was hypothesized in this study that there would be an effect of aircraft type on the human factors findings for MQ-1 Predator and MQ-9 Reaper RPA mishaps.

3. Methods

Institutional Review

This study was conducted under a human-use protocol approved by the 711th Human Performance Wing Institutional Review Board and in accordance with Federal and USAF regulations on the protection of human subjects in biomedical and behavioral research.

Study Design

This study was a cross-sectional survey of the population (N = all) of human factors-related MQ-1 and MQ-9 RPA mishaps occurring during the period from October 1, 2005, through September 30, 2011. Inclusion criteria were a mishap with direct costs totaling $20,000 or more and for which there was a safety investigation and report archived in the Air Force Safety Center (AFSEC) database with associated Department of Defense (DoD) Human Factors Analysis and Classification System (HFACS) nanocodes (a description of DoD HFACS and the associated nanocodes is available at http://www.uscg.mil/safety/docs/ergo_hfacs/hfacs.pdf). The HFACS coding was used as recorded in the AFSEC database without augmentation by the study investigators.

Study Dataset

The data extracted from the AFSEC database were cleaned and organized into a deidentified study dataset by one of the study investigators. The study dataset consisted of a spreadsheet in which each row was a mishap and each column corresponded to an HFACS nanocode. Within this matrix, each cell was annotated with either a zero or one depending on whether the corresponding HFACS nanocode was cited by the original investigators as being present in the corresponding mishap. Given the sparseness of findings at the nanocode level, the nanocodes were subsequently consolidated into HFACS subcategories at the *acts/errors* and *preconditions* tiers and categories at the *acts/violations, supervision,* and *organizational influences* tiers. A column was thus added to the spreadsheet for each HFACS subcategory or category. As before, each cell was then annotated with either a zero or one depending on whether any corresponding nanocodes were present for that HFACS subcategory or category for the associated mishap.

Statistical Analysis

In formulating a perspective for studying the influence of aircraft heterogeneity on the human performance challenges when operating an RPA from the same control station—that is, varying aircraft and holding the human-machine interface constant—there is both a theoretical and nontheoretical approach. In the theoretic or systems approach, we accept the basic premise that humans are fallible and errors are to be expected. Errors are then conceptualized as consequences, rather than causes, having their origins in antecedent systemic factors. Such factors include error traps in the workplace and the organizational practices that give rise to them (3).

This theoretical framework has been popularized in Reason's "Swiss Cheese" model of human error, which was later expanded upon by Wiegmann and Shappell (6) to develop their HFACS. Briefly, Reason's model implies that active failures (e.g., human errors and volitional violations) result from contributory latent failures at all levels with an organization. Ultimately both active and latent failures must be addressed for any accident prevention program to be expected to have a significant impact on safety and improve human performance. HFACS expounds upon Reason's model by providing an associated taxonomy for active and latent failures. When looking across sets of mishaps described using HFACS, based on theory, we expect to see recurring associations between active and latent failures. The rationale is that latent failures tend to be relatively enduring, and thus recurring sets of circumstances tend to provoke similar errors regardless of the individuals involved (5).

This theoretical framework was operationalized in the present study by constructing logistic regression models that considered latent failures as potential predictor variables of active failures. The effect of aircraft was then included in the models as both an independent predictor variable and a potential modifier of the effect of predictor variables for latent failures. The full logistic regression models took the following general form:

$$\text{logit}(ACT_k) = B_0 + B_1 ACFT + \sum_{i=1}^{16} B_{i+1} LATENT_i + \sum_{j=1}^{16} B_{j+17} LATENT_j \cdot ACFT \quad \forall\, k = 1 \ldots 4$$

where ACT_k is an indicator variable for the presence of an act of type *k* (there are four types of acts in HFACS), $ACFT$ is an indicator variable for aircraft type (0 = MQ-1, 1 = MQ-9), and $LATENT_j$ is an indicator variable for the presence of a latent failure of type *j* (i.e., failures at the levels of preconditions, supervision, and organizational influences). The final fitted modes for each type of active failure were obtained using stepwise regression.

We also adopted a nontheoretic approach in this study based on factor analysis. Factor analysis has no independent variables or dependent variables; it is a form of data reduction that seeks underlying unobservable variables that are reflected in observed variables—that is, it seeks to surface hidden structure in the data. In the present study, we elected for a relatively straightforward factor analysis and used principal component analysis as the method of extraction and a varimax rotation, which imposes the restriction that the factors cannot be correlated.

4. Results

In total, 88 human factors-related MQ-1 and MQ-9 RPA mishaps were identified in the AFSEC dataset. A summary of the prevalence of HFACS categories/subcategories in those mishaps is summarized in Table I. Crude associations between aircraft type and HFACS categories/subcategories were assessed using χ^2 tests; only a single borderline significant association was observed for cognitive factors (p = 0.062).

Table 1. Prevalence of HFACS categories/subcategories in human factors-related MQ-1 and MQ-9 RPA mishaps.

HFACS Tier and Categories/Subcategories	**MQ-1 Mishaps (n=69)**		**MQ-9 Mishaps (n= 19)**		**Chi-Square or Fisher's Exact *p*-value**
	Number	**Percent**	**Number**	**Percent**	
Acts					
Skill-based errors	34	49.3	12	63.2	0.283
Judgment and decision-making errors	25	36.2	5	26.3	0.419
Misperception errors	11	15.9	6	31.6	0.126
Violations	1	1.4	0	0.0	>0.999
Preconditions					
Physical environment	1	1.4	0	0.0	>0.999
Technological environment	25	36.2	6	31.6	0.707
Cognitive factors	27	39.1	12	63.2	0.062
Psycho-behavioral factors	16	23.2	5	26.3	0.777
Adverse physiological states	8	11.6	2	10.5	>0.999
Physical/mental limitations	4	5.8	2	10.5	0.606
Perceptual factors	18	26.1	5	26.3	0.984
					0.455
Coordination/communication/planning factors	16	23.2	6	31.6	
Self-imposed stress	2	2.9	0	0.0	>0.999
Supervision					
Inadequate supervision	17	24.6	4	21.1	>0.999
Planned inappropriate operations	15	21.7	6	31.6	0.373
Failure to correct known problem	2	2.9	1	5.3	0.523
Supervisory violations	6	8.7	2	10.5	>0.999
Organizational influence					
Resource/acquisition management	32	46.4	7	36.8	0.459
Organizational culture	8	11.6	5	26.3	0.109
Organizational process	42	60.9	8	42.1	0.144

Logistic Regression Analysis

Table II summarizes the final fitted models for each of the categories/subcategories of acts. The model for violations only included an intercept term and so it is not shown in the table. No model included the variable for aircraft, either as an independent term or as an interaction effect with one of the other HFACS categories/subcategories of latent failure. Accordingly, we reject our hypothesis that there is an effect of aircraft type on the human performance challenges when operating an RPA from the same control station. In addition, the absence of the variable for aircraft in any model also suggests that there was no difference in the relative likelihood for specific active failures (i.e., skill based, judgment and decision-making, and misperception errors) in the MQ-1 versus the MQ-9 RPA. This observation was also confirmed directly using a chi-square analysis to compare the observed versus expected counts for each type of error in the MQ-1 and MQ-9 RPA ($\chi^2_{2\ \mathrm{df}}$ = 2.113, p = 0.348). Attributes of the control station design (i.e., the technological environment) increased the likelihood of both judgment and decision-making and misperception errors, with the effect being approximately twice as great for misperception errors.

Table 2. Fitted logistic regression models for the categories/subcategories of acts.

Variable	**Regression Coefficient**	**Standard Error**	**Odds Ratio**	**95% Confidence Interval for Odds Ratio**		***p*-value***
				Lower	**Upper**	
Model for skill-based errors:						
Intercept	-0.544	0.296				
Cognitive factors	1.478	0.463	4.384	1.769	10.865	0.001
Model for judgment and decision-making errors:						
Intercept	-1.572	0.370				
Technological environment	1.140	0.505	3.126	1.161	8.417	0.024
Coordination/ communication/ planning factors	1.661	0.547	5.263	1.800	15.383	0.002
Model for misperception errors:						
Intercept	-3.450	0.675				
Perceptual factors	2.380	0.680	10.804	2.849	40.968	0.001
Technological environment	2.048	0.701	7.749	1.961	30.615	0.004

*Wald χ^2 test.

Factor Analysis

Based on the exploratory factor analysis, it was possible to reduce the study dataset to eight factors while still accounting for 65% of the variance in the original dataset (Table III). A factor analysis only uncovers latent mathematical structure within a set of variables, leaving it to the researchers to infer the meaning of the factors. However, rather than discussing each factor in detail here, it suffices for the purpose of the objective of this study to primarily note that the aircraft variable was associated with only one latent failure at the organizational influences tier (i.e., organizational process). The aircraft variable was not associated with any of the variables representing active failures or latent failures at the preconditions tier, the latter including factors addressing attributes of the control station environment and the adverse effects of the control station environment on the crew. Consequently, as in the logistic regression analysis, we reject our hypothesis that there is an effect of aircraft type on the human performance challenges when operating an RPA from the same control station.

Table 3. Results of the factor analysis of the 88 MQ-1 and MQ-9 RPA human factors-related mishaps.

Factor	Cumulative Variance (%)	Items Included	Factor Loading
1	9.94	Misperception errors	0.790
		Perceptual factors	0.742
		Technological environment	0.660
2	19.50	Organizational culture	0.834
		Planned inappropriate operations	0.727
		Resource/acquisition management	0.660
3	28.37	Skill-based errors	0.701
		Coordination/communication/planning factors	0.602
		Judgment and decision-making errors	0.460
4	36.86	Physical environment	0.775
		Physical/mental limitations	0.722
5	45.27	Psycho-behavioral factors	0.760
		Inadequate supervision	0.686
		Supervisory violations	0.599
		Cognitive factors	0.467
6	53.18	Self-imposed stress	0.846
		Adverse physiological states	0.718
7	59.68	Aircraft	0.806
		Organizational process	-0.493
8	65.44	Failure to correct known problem	0.730
		Violations	-0.530

5. Discussion

The objective of this study was to take advantage of a natural experiment and utilize readily available mishap data to gain insight into the impact of RPA heterogeneity on the human performance challenges when operating an RPA from the same control station—that is, varying aircraft and holding the human-machine interface constant. It was our presumption that if aircraft type imparted differential demands on the RPA pilot, then aircraft type would explain some variability in the prevalence of mishap human factors findings. The statistical analysis utilized two approaches: (1) logistical regression models that were formulated based on the theoretical assumptions underlying HFACS and (2) a factor analysis that relied on no a priori theoretical assumptions. Regardless of analytic approach, we reached the same conclusion, namely, that there was no effect of aircraft type on the human performance challenges when operating an RPA from the same control station. To the best of the authors' knowledge, this is the first study to demonstrate this finding for RPA.

While the results of this study should help inform the choice of approach for recommending medical standards for RPA pilots, it is important to note the potential limitations of this study. Foremost, the differential effect of aircraft type between the MQ-1 Predator and MQ-9 Reaper RPA may have been too small to detect a difference given the available number of mishap cases—that is, a false negative or type II error. While these aircraft are similar in appearance, they are in fact quite different in performance. For example, the MQ-1 Predator has an engine that produces 115 hp of thrust and the aircraft weights 1,130 lb, cruises at 84 mph, and has an operational ceiling of 25,000 ft. In contrast, the MQ-9 Reaper has an engine that produces 900 hp of thrust and the aircraft weights 4,900 lb, cruises at 230 mph, and has an operational ceiling of 50,000 ft. However, it remains to be demonstrated if the absence of an effect of aircraft type would be observed if the comparison involved a smaller and less complex tactical RPA system. This issue highlights an important limitation of natural experiments in which the investigator does not control the variable settings.

Nonetheless, the cardinal issue with which regulators responsible for promulgating RPA pilot medical standards will need to grapple is the disconnect between the terrestrial work environment of the RPA pilot and the operational environment of the aircraft. The results of this study suggest that the terrestrial work environment should be a primary consideration in determining the medical standards for the RPA pilot. Such an assertion is relatively intuitive when considered from an aerospace human factors as well as an occupational medicine perspective—the terrestrial work environment defines the job essential tasks and the physical and cognitive demands on the RPA pilot. The challenge for the regulator can then be framed in terms of the principle of requisite variety (2), which implies that any set of medical standards must have sufficient variability to match the variety of terrestrial RPA work environments that are to be regulated. However, the observed absence of an aircraft effect could also be a potential simplifying factor for regulators. Since future RPA operators will have the ability to purchase control stations and aircraft as distinct products and potentially mix and match them in the process on conducting daily operations, medical standards that need to account for both the terrestrial work environment and the operational environment of the aircraft would significantly increase the complexity of the regulatory space. Similarly, the predominance of the terrestrial work environment in medical standards would alleviate the regulatory challenge of the scenario where an RPA pilot is simultaneously controlling multiple types of aircraft.

Another consideration in determining the medical standards for the RPA pilot is the need to protect the public from occupations that involve operations where public safety is potentially at risk, such as transportation. Medical standards for such occupations are not based solely on an analysis of physical and cognitive task demands of the work environment; they also may address the risk of impairment or incapacitation due to the pathology or treatment of any preexisting medical conditions. The establishment of an acceptable level of risk is a function of those responsible for public policy. Once acceptable public risk is defined, the function of the medical and scientific community is one of quantifying an individual RPA pilot's risk to determine whether he or she may exceed this arbitrary threshold. Again, RPAs have the potential to add a wrinkle to the regulator's normal calculus. For example, what is the risk to public safety of RPA pilot incapacitation when the pilot is a member of a distributed team of pilots on a network sharing responsibility for the operation of many heterogeneous RPAs involved in a variety of operations? The challenge now becomes one of overall network reliability where the individual RPA pilot is one of *n* elements comprising the network.

This discussion should highlight the need to start creatively thinking about the aeromedical issues that will arise as RPA technologies are increasingly used in our military and civil aviation operations. This technology, and the prospect of future networked control of heterogeneous RPAs, is inherently disruptive to current paradigms, and so attempts to fit RPA medical standards within established medical requirements for other occupations is not likely to be successful in the future. Given that RPAs are largely dependent of computer technology, the latter of which demonstrates exponential progress as encapsulated in "Moore's law," we must devise approaches that are inherently accommodating of change.

6. Conclusions

The present study demonstrated that variation in aircraft type did not impart differential demands on the RPA pilot using a common control station as evidenced by the absence of an aircraft effect on the variability in the prevalence of human factors findings in MQ-1 Predator and MQ-9 Reaper RPA mishaps. This observation suggests that the terrestrial work environment should be a primary consideration in determining the medical standards for the RPA pilot. However, these findings need to be validated across a wider spectrum of aircraft types.

REFERENCES

1. Biggerstaff S, Blower DJ, Portman CA, Chapman AD. The development and initial validation of the unmanned aerial vehicle (UAV) external pilot selection system. Pensacola, FL: Naval Aerospace Medical Research Laboratory; 1998 Aug. Report No.: NAMRL-1398.

2. Pidd M. Tools for thinking: 10odeling in management science, 3rd ed. Chichester, England: John Wiley and Sons; 2009:64.

3. Reason J. Human error: models and management. *BMJ* 2000; 320:768–70.

4. Tvaryanas AP. The development of empirically-based medical standards for large and weaponized unmanned aircraft system pilots. Brooks City-Base, TX: 311th Performance Enhancement Directorate; 2006 Oct. Report No.: HSW-PE-BR-TR-2006-0004.

5. Tvaryanas AP, Thompson WT. Recurrent error pathways in HFACS data: analysis of 95 mishaps with remotely piloted aircraft. *Aviat Space Environ Med* 2008; 79:525–32.

6. Wiegmann DA, Shappell SA. A human error approach to aviation accident analysis: the Human Factors Analysis and Classification System. Burlington, VT: Ashgate; 2003:45–70.

7. Williams KW. Unmanned aircraft pilot medical certification requirements. Oklahoma City, OK: Civil Aerospace Medical Institute; 2007 Feb. Report No.: DOT/FAA/AM-07//

APPENDIX
ACRYNOMS

AFSEC	Air Force Safety Center
DoD	Department of Defense
HFACS	Human Factors Analysis and Classification System
MQ-1	MQ-1 Predator
MQ-9	MQ-9 Reaper
RPA	Remotely Piloted Aircraft
USAF	United States Air Force