Exploring Relationships of Human-Automation Interaction Consequences on Pilots: Uncovering Subsystems

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Objective: We attempted to understand the latent structure underlying the systems pilots use to operate in situations involving human-automation interaction (HAI).

Background: HAI is an important characteristic of many modern work situations. Of course, the cognitive subsystems are not immediately apparent by observing a functioning system, but correlations between variables may reveal important relations.

Method: The current report examined pilot judgments of 11 HAI dimensions (e.g., Workload, Task Management, Stress/Nervousness, Monitoring Automation, and Cross-Checking Automation) across 48 scenarios that required airline pilots to interact with automation on the flight deck.

Results: We found three major clusters of the dimensions identifying subsystems on the flight deck: a workload subsystem, a management subsystem, and an awareness subsystem.

Discussion: Relationships characterized by simple correlations cohered in ways that suggested underlying subsystems consistent with those that had previously been theorized.

Application: Understanding the relationship among dimensions affecting HAI is an important aspect in determining how a new piece of automation designed to affect one dimension will affect other dimensions as well.

Keywords: automation, aviation and aerospace, pilot decision making, human-automation interaction, automation, expert systems, cognitive structure, cognition, knowledge elicitation/acquisition, methods and skills

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INTRODUCTION

Researchers in human factors have spent considerable theoretical and empirical effort understanding how human operators interact with automation (Sheridan & Parasuraman, 2006). On the flight deck, pilots plan ahead, instruct the flight management system (FMS), monitor flight progress, correct and modify flight paths, and learn from their aircraft's reactions (Billings, 1996; Chou, Madhaven, & Funk, 1996; Wickens, 2002). Pilots decide when to engage and disengage automation, which automation to use, the extent to which they should monitor and cross-check the automation, and so on (Colvin, Funk, & Braune, 2005; Dismukes, 2001; Funk, 1991; Wickens, 2002).

For the current research effort, we consider pilots' perception of human-automation interaction (HAI) situations to be a function of the automation, the task, the context, and the pilot. That is, HAI = *f* (automation, task, context, and pilot). We conducted extensive interviews with a small group of commercial airline pilots and asked them to respond to a series of 48 scenarios. The scenarios were based on aviation system reporting system (ASRS) incident reports related to HAI and represented a wide sampling of situations pilots encounter when nearing an airport, one of the highest workload segments of flight, requiring smooth crew interaction with automation.

We were interested in the consequences of HAI from the pilots' perspective. Although expert pilots may not be able to identify the components and subsystems of HAI directly, we wanted to explore the possibility that making simple judgments could allow the subsystems that influenced the pilot to emerge. Thus, we designed this study to explore the assumption that judgments from expert pilots could reveal the underlying relationships that held together the system that allowed humans and automation to land commercial airliners.

The current study was exploratory. We were trying to determine the relationship among critical psychological and behavioral dimensions. By understanding the relationship among the dimensions, we hope to provide some evidence for how a piece of automation designed to affect one of these dimensions could influence another of the dimensions. Understanding how these dimensions are related will help us to better understand how changes in automation will not only influence individual dimensions but clusters of related dimensions as well. In other words, it would reveal the underlying subsystems by identifying the relationships that bind the dimensions together.

A system can be distinguished from "just a bunch of stuff" (Meadows, 2008) by whether it has identifiable parts that affect each other and produce an effect that differs from the effect of the part in isolation. Further, this behavior over time persists in a variety of circumstances. By studying the relations among pilots' judgments of HAI dimensions in a variety of circumstances, we hope to begin to shed light on the systems that underlie pilot perceptions of HAI situations.

In a previous study (Mosier e al., 2013), we investigated the relationship among a few dimensions in two HAI situations. The goal of that study was to examine how variations of automation interface, task features, and context features influenced pilots' judgments of HAI situations. The current report examined a larger number of HAI dimensions across a larger number of flight situations with the purpose of gaining insight into the underlying subsystems of HAI.

METHOD

Participants

Participants were 12 commercial airline pilots. They were paid $500 for two days of their time. Nine pilots, one of whom was retired, flew for Delta Airlines, two pilots for AirTran Airways, and one pilot for Atlantic Southeast Airlines. The 11 currently active pilots had an average flying time of 3,168 hours (250–9,500 hours) in their current aircraft. The average total flying time for all 12 pilots was 14,075 hours (6,400–25,000 hours).

Scenario Construction and Characterization

A set of 48 flight scenarios was created for this study. The scenarios were based on 12 incident reports from the ASRS involving HAI issues related to current generation automation during arrival and approach. The scenarios were first condensed into short paragraphs presenting only conditions and crew actions prior to the focal incident—without including the incident. These 12 primary or "parent" reports ultimately were tweaked to create three "children," or variants of the scenario. For example, Parent 1 describes a situation in which the crew deletes a speed restriction using an FMS that requires multiple steps.

> A B737-700 is on the GEELA 2 Arrival into PHX. It was night and conditions were VMC. ATC has cleared the flight to descend via the arrival and then instructed crew to delete the speed restrictions. Pilot monitoring wants to delete the speed on the CDU. In order to do so, he deletes the whole line and subsequently has to re-enter the altitude. (GEELA2 = an arrival into PHX [Phoenix]; VMC = visual meteorological conditions; CDU = cockpit display unit)

In Child 1A, the crew deals with the speed restriction deletion using speed intervention. Child 1B adds time pressure and traffic to the scenario. Child 1C introduces terrain issues by changing the airport and reducing visibility. Refer to Tables 1 and 2 for a complete description of the 12 parent scenarios. See HART Group (2012) for a complete description of the 12 parent scenarios and 36 children.

Dimensions of Pilots' Judgments

Based on our review of the literature (see HART Group, 2011), a focus group of human factors specialists, and interviews with pilots, we identified a preliminary set of 11 critical

TABLE 1: Parent Scenarios 1 Through 6

Parent	Scenario Description
1	A B737-700 is on the GEELA 2 Arrival into PHX. It was night and conditions were VMC. ATC has cleared flight to descend via the arrival and then instructed crew to delete the speed restrictions. Pilot monitoring wants to delete the speed on the CDU. In order to do so, he deletes the whole line and subsequently has to re-enter the altitude.
2	A B757-200 is on the SEAVU arrival into LAX and has been cleared to cross KONZL at 17,000 FT. Earlier during descent, the pilot flying decided to switch from VNAV to vertical speed because VNAV had started descent too early. Approximately 5 NM from KONZL, as the aircraft was approaching 17,000 FT, but was not yet in altitude hold, ATC changed runway assignment to 25L and at the same time cleared the flight for the descent via the arrival. In response to ATC clearance, the pilot monitoring starts to reprogram the FMS for the new runway, and the pilot flying enters the next altitude in the MCP window.
3	At FL 360, a B737-300 was cleared to descend to FL 340 and then to cross 85 NM east of PGS at FL 300. It took the crew a long time to input this clearance into the FMC since two waypoints (BAVPE and CUTRO) were between PGS and the 85 NM fix. As a result the crossing restriction showed up prior to BAVPE, CUTRO, then PGS. Crew subsequently obtained ATIS, calculated the numbers on the performance computer, and briefed the approach and landing in LAS. After completing these tasks, the pilot flying wants to verify distance to the top of descent point and looks at the Descent page.
4	A B737-700 was inbound to LAX on the RIIVR 2 Arrival from FL 190 approximately 2 miles from RUSST when ATC issued a runway assignment different from what had already been programmed into the FMC. Aircraft is in LNAV, VNAV, and autothrottle is engaged. As the pilot monitoring was programming in the new runway, ATC issued another airspeed change. The pilot flying programs the new speed into his CDU and executes the change.
5	The crew of a B737-700 was told to descend via the RAVNN 3 Arrival into BWI. Passing around 16,500 FT at a vertical rate of around 3,000 FPM, the aircraft was established on the arrival and south of the SABBI intersection, which has a crossing restriction of 15,000 FT. The aircraft is in LVL CHG mode when the pilot flying sets 6,000 FT in the altitude window. This is the last published altitude on arrival over RAVNN.
6	A B737NG was on VNAV descent via the SEAVU Arrival into LAX just prior to PECOX intersection, when ATC assigned a speed of 290 KTS. The pilot flying needs to hit the speed intervention button and set speed to 290 KTS to ensure that the aircraft complies with the crossing restriction at PECOX.

psychological and behavioral dimensions for pilots to judge in the HAI scenarios developed for this study. All of these dimensions represented important factors in aviation, including NextGen operations. The dimensions were: Workload, Task Management, Stress/Nervousness, Monitoring Automation, Cross-Checking Automation, Awareness of the Automation's State (AA), Situation Awareness (SA), Probability of an Automation-Related Error, Interaction With the Automation, Crew Coordination, and Air Ground Communication. Pilots could ask questions about terms and definitions as needed and responded to each question for each parent and child scenario.

Pilots were asked to rate the amount of each dimension that was present on a 7-point rating scale, with 1 being very low and 7 being very high, in each of the 48 scenarios. Table 3 presents the list of questions asked of pilots for each of the 11 dimensions.

Procedures

Pilots participated in a two-day intensive interview during which time they answered questions about the 48 scenarios. In addition

TABLE 2: Parent Scenarios 7 Through 12

Parent	Scenario Description
7	A B737-700 was cleared to cross KADDY at 12,000 and then to descend via the TYSSN THREE RNAV Arrival. Eight thousand FT was the selected altitude in the window for the VNAV descent. Center then issued a clearance to fly normal speed until KADDY. The pilot flying wants to pick up speed until KADDY. He knows that he will have to get below the depicted glide in order to slow for the 250 KT restriction at KADDY. He therefore needs to de-select VNAV and select vertical descent. He also needs to de-select the autothrottle and change the altitude alerter to the next restriction altitude as required when de-selecting VNAV. At the same time pilot monitoring points out that there is ice on the wings and suggests to turn on the wing anti-ice.
8	A B737-800 was on ILS for Runway 04 at LaGuardia. ATIS indicated wet runways, low ceiling and visibility, and that LGA Tower was also utilizing Runway 13/31. During their approach briefing, crew talked about the possibility of a runway incursion or that visibility/ceiling could be lower than advertised. In anticipation of a possible missed approach/go-around, pilot flying has his fingers very close to the TO/GA Buttons as the aircraft reaches minimums.
9	After contacting approach, the crew of a B737 was assigned runway 26. The pilot monitoring proceeds to extend the centerline on the FMC. The rubber type buttons are worn out and he has a difficult time getting the 6R button to take the runway heading.
10	A B737-700 is cleared for a visual approach and turns right base to final in heading select mode. At 8.5 DME, the aircraft was configured at flaps 5, 180 KIAS, autopilot/autothrottles were engaged, and approach mode armed. Crew was then given a descent from 4,000 feet to 2,500 feet AGL, which the pilot flying executed in level change. ATC also instructed crew to follow traffic. While the pilot flying is looking outside for the traffic and runway alignment, the autothrottle becomes disengaged, the autothrottle warning light flashes, and the autothrottle symbol disappears on the FMA.
11	An MD-80 was on initial approach about 50 miles from the field. It was a clear night with unlimited visibility. The crew received clearance direct FAF, ILS runway 22. Magenta line showed direct and the aircraft proceeded toward the FAF in NAV. At some point the FMS reverts to the Dead Reckoning mode, and the DR cue appears in the PDF. The course looks accurate to the crew visually.
12	During a managed VOR\DME approach to runway 23R at EGCC crew of an A340 realizes that the approach specifications included in the database do not correspond to the approach plate. After verifying with ATC that they show the aircraft on course, the pilot flying switches to open descent (flight level change).

to responding to the 11 rating scales reported here, they were engaged in conversations about the details of the scenarios and provided open answer responses to queries about the role of automation—for good or ill—in the scenario. Most pilots completed all tasks in 7 to 8 hours spread over the two days. Only the responses to the rating scale items are discussed in this report. Other details are available in HART Group (2012).

RESULTS

Pilot responses were averaged across the 48 scenarios, producing a vector of 11 mean judgments for each pilot. Intercorrelations among the 11 judgments were then calculated for this analysis. The Pearson correlations appear in Table 4.

To begin, we needed a principled way to decide on the number of relationships that would characterize the pilots' judgments in a way that

TABLE 3: Human-Automation Interaction Dimensions: What Pilots Were Asked to Rate

Dimension	Question
Workload	How much mental workload would the crew experience in this specific scenario with its particular tasks and use of automation?
Stress	How much stress or nervousness would the crew experience in this specific scenario with its particular tasks and use of automation?
Air Ground Communication	How much air/ground communication was needed in this specific scenario with its particular tasks and use of automation?
Crew Coordination	How much crew coordination was needed in this specific scenario with its particular tasks and use of automation?
Task Management	How much time or effort would be required to manage the tasks in this specific scenario with its particular tasks and use of automation?
Interaction With Automation	How much interaction with the automation was needed in this specific scenario with its particular tasks and use of automation?
Cross-Checking Automation	How much cross-checking of the automation would the crew do in this specific scenario with its particular tasks and use of automation?
Monitor Automation	How much monitoring of the automation would the crew engage in with this specific scenario and its particular tasks and use of automation?
Probability of an Automation Related Error	How likely would it be to have an automation related error in this specific scenario with its particular tasks and use of automation?
Situation Awareness	How much situation awareness (SA) would the crew have in this specific scenario with its particular tasks and use of automation?
Awareness of Automation State	What level of awareness of what the automation is and will be doing would the crew have in this specific scenario with its particular tasks and use of automation?

would reveal interesting structures in the pilots' system and subsystems. Of course, with a very liberal p value, all of the interrelations will qualify. Identifying innumerable relationships among the dimensions may confirm the interrelatedness of the overall system but does little for identifying the subsystems. With a very conservative p value, none of the relations will be included. We wanted to pick a p value that would highlight a rich number of interrelationships but such a number as to be illuminating.

We plotted the number of relations that met a significance level as a function of that significance level. That plot appears in Figure 1. We looked for an elbow in the function that indicated a large increase in the number of relations for a relatively small change in the p value. This elbow criterion suggested that a p value of .01 produced a rich correlation structure. An equivalent increase in complexity would require a substantially more liberal significance level.

There were 19 correlations significant at the .01 level in this analysis. These correlations appear in the graph depicted in Figure 2. All correlations were positive. Thus, a correlation between Monitoring Automation and SA indicates that an increase in monitoring of automation is related to an increase in SA. Of the 11 outputs, two pairs shared all of the same significant correlations. Crew Coordination and Task Management shared all the same significant correlations as well as a significant correlation with each other ($r = .809$). AA and SA likewise shared all the same significant correlations as well as a significant correlation with each other ($r = .956$). This suggests that in the scenarios used for this analysis, anything that affected one of these outputs within a pair also affected the other output within the same pair. The two pairs of concepts discussed previously with comparable correlations appear in boxes in Figure 2. Essentially, for these data, the two terms within a box are

TABLE 4: Participant-Based Correlations of the 11 Critical Psychological and Behavioral Dimensions

	Workload	Monitoring of Automation	Task Management	Stress	Awareness Automation State	Cross-Checking	Situation Awareness	Automation-Related Error	Interaction With Automation	Crew Coordination	Air-Ground Communication
Workload		.842**	.931**	.583*	.634*	.719**	.664*	.043	.625*	.819**	.418
Monitoring of Automation	.842**		.890**	.685*	.768**	.952**	.780**	.442	.712**	.782**	.383
Task Management	.931**	.890**		.499	.621*	.771**	.637*	.34	.726**	.809**	.433
Stress	.583*	.685*	.499		.612*	.782**	.617*	.23	.587*	.656*	.305
Awareness Automation State	.634*	.768**	.621*	.612*		.818**	.956**	.266	.439	.545	.222
Cross-Checking	.719**	.952**	.771**	.782**	.818**		.844**	.472	.690*	.718**	.471
Situation Awareness	.664*	.780**	.637*	.617*	.956**	.844**		.226	0.46	0.552	.391
Automation-Related Error	.043	.442	.34	.23	.266	.472	.226		.630*	0.317	.015
Interaction with Autom.	.625*	.712**	.726**	.587*	.439	.690*	.46	.630*		.899**	.425
Crew Coordination	.819**	.782**	.809**	.656*	.545	.718**	.552	.317	.899**		.448
Air-Ground Communication	.418	.383	.433	.305	.222	.471	.391	.015	.425	.448	

*Effect was significant at $\alpha = .05$.
**Effect was significant at $\alpha = .01$.

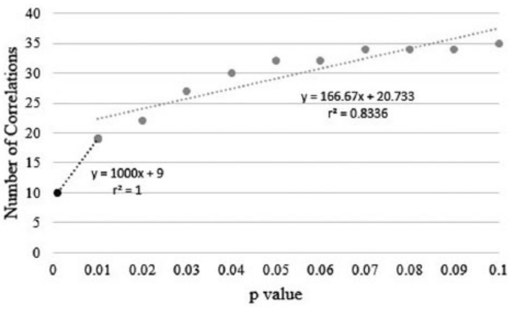

Figure 1. Plot showing the number of correlations at p values .001 to .1. To determine the elbow in the function, all possible pairs of linear regressions were computed. The best fit pair of lines are depicted in the figure, defining the elbow at $p = .01$.

equivalent, although they may represent distinct constructs more generally.

The figure highlights three cliques. A clique represents a group of nodes that are all correlated with each other. A clique implied to us that these characteristics are so intimately interdependent that it would be useful to interpret them as one higher-order subsystem. We discuss three cliques, each comprising several smaller cliques. Systems have as a fundamental property a hierarchical organization (Meadows, 2008). The cliques can be viewed as subsystems within a hierarchy that yields the overall graph depicted in Figure 2.

The first clique (represented by dashed connections in Figure 2) includes four outputs: Crew Coordination, Task Management, Interaction With Automation, and Monitor Automation. This clique is suggestive of a management subsystem comprising both the human crew and the automation. The management subsystem seemed to be associated with aspects of the task that require taking actions that require decision making and strategy selection: how and when to interact with the automation, monitor the automation, and deal with the crew and the task. The ability to assess the various components and then decide on the strategy to use is a key to resilient systems.

The second clique (represented by dotted connections in Figure 1) includes four outputs: SA, AA, Monitor Automation, and Cross-Checking

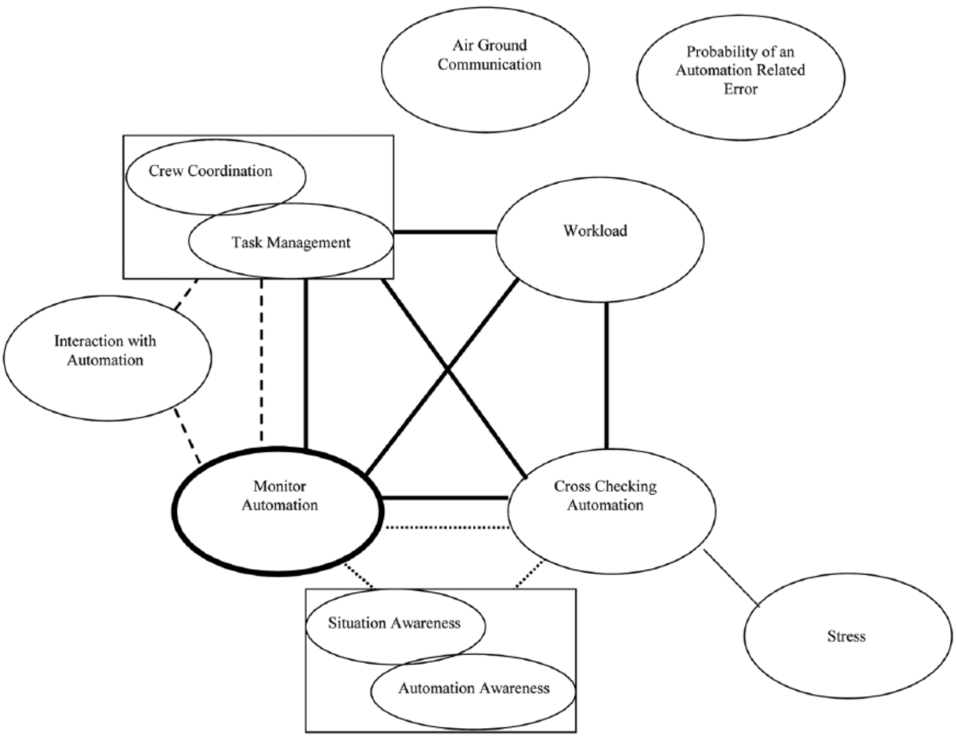

Figure 2. Intercorrelations of the 11 critical psychological and behavioral dimensions among 12 pilots.

Automation. This clique is suggestive of an awareness subsystem wherein the human monitors the automation in an effort to maintain awareness of the situation, including assessing the state of the automation. It is interesting to note that although AA and SA correlate to both monitor automation and Cross-Checking Automation, they do not correlate to Interaction With Automation. Neither SA nor AA connects to Interaction With Automation in versions of the graph based on considerably more liberal p values (e.g., $p < .1$). In fact, SA does not connect to Interaction With Automation until $p = .133$, and AA does not connect to Interaction With Automation until $p = .153$. The lack of a strong connection to Interaction With Automation suggests this clique is most properly considered a monitoring subsystem. Cross-checking and monitoring of the automation relate to how much awareness (SA and AA) the pilot would have.

The third clique (represented by bold connections in Figure 1) includes five outputs: Crew Coordination, Task Management, Workload, Monitor Automation, and Cross-Checking Automation. This clique seems to interrelate all of the pilot issues that have a direct impact on his or her workload. Not surprisingly, some of these concepts are shared in other subsystem cliques but none of the other subsystems highlights workload. Thus, we tentatively relate the subsystem to workload. How much cross-checking of the automation was required, how much monitoring of the automation was required, how much crew coordination was required, and how much time or effort on task management was required all relate to how much workload would be required. Thus, we interpret this clique as a workload subsystem.

Monitor Automation (circled in bold) is the most integral part of the graph. It is the graph-theoretic center and is the only scale represented in all three cliques. The three subsystems seemed joined through the monitor automation concept.

Three scales are either isolated from or weakly connected to the main cluster. Stress is only correlated to Cross-Checking Automation. Thus, only the concept of double checking automation against other information sources is related to stress in these data. Air Ground Communication and Probability of an Automation Related Error are isolated from all other scales. This means that there is not a simple, one variable correlation with either of these concepts and the rest of the graph.

DISCUSSION

The analyses discussed in the current report established that the dimensions of pilot judgments we considered seem to coalesce into some interrelated clusters, perhaps reflecting subsystems of flight deck activity, as well as some judgments that seemed to capture other dimensions. There was a large collection of variables dealing with workload-related concepts, management-related concepts, and awareness-related concepts.

These same subsystems were identified by Durso and Alexander (2010) while discussing aviation. By identifying and understanding these subsystems, one may be able to better understand how a piece of automation will affect the pilot's management, awareness, and workload in HAI situations. For example, the current research has been used to develop a neural network (Sullivan et al., 2013) that can take in a set of inputs (HAI characteristics) and predict a set of outputs (psychological and behavioral dimensions) to access the impact a piece of automation will have on HAI.

Parasuraman, Sheridan, and Wickens (2008) also identified three subsystems: workload, SA, and trust. The overlap with Durso and Alexander (2010) suggests that workload and SA are receiving some consensus as important subsystems of human-automation interaction. Juxtaposing Durso and Alexander's management subsystem and Parasuraman et al.'s trust subsystem suggested to us that the two subsystems may not be as different as the names suggest. Intuitively our processing and assessment of trust, whether in the automation we use or in the colleagues with whom we work, affects the management approach we take. For example, we may micromanage employees we do not trust, repeatedly requesting reports from them, but we may give trusted employees free reign, instead waiting for the employees to report to us when they are ready.

Future research should continue to investigate the subsystems in HAI that accompany workload and SA. In particular, a subsystem that involves management and the processes that affect it (like trust) seem like viable candidates for further consideration.

Other relations revealed in the correlation network were also revealing. For example, situation awareness was clearly viewed by the pilots as a cognitive construct that was not connected to any node representing actions. The figure gives the impression that pilots have segmented their understanding of the situation and automation from the actions they take when interacting with the automation. Of course, within the overall system, such relations are present, but they were not, in this study, primary or direct relationships. Action and cognition seem to be captured by different subsystems that eventually interrelate in the system of systems.

Finally, leveraging the intercorrelations among pilot judgments yielded some success in identifying subsystems, suggesting that using correlations may prove to be a viable way to conduct exploratory analysis of subsystems. The cliques tended to suggest meaningful subsystems. The intercorrelation graphs supply details about specific components within a subsystem. They also help us understand how subsystems are connected. For example, the Monitoring subsystem connects to the Workload subsystem at Cross-Checking Automation and Monitor Automation. All three subsystems connect at Monitor Automation, although virtually every dimension we explored in this study was about automation, and thus any dimension could have served such a central role.

The fact that Monitor Automation plays such a central role in the organization of subsystems perceived by pilots in HAI has several implications. It confirms that the discipline's interest in the human's ability to monitor automation and its relationship to workload, situation awareness, and management is well founded. It also suggests that changes in automation that affect automation monitoring are likely to have the most complex effects on HAI because automation monitoring overlaps and influences a multitude of HAI dimensions.

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KEY POINTS

- Airline pilot judgments made during human-automation interaction scenarios correlated in systematic ways.
- The correlation structure suggested three subsystems that were consistent with those previously suggested in the literature: workload, awareness, and management.
- Monitoring automation was the nexus that bound the latent subsystems.

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