International Journal of Occupational Safety and Ergonomics (*JOSE*) 2014, Vol. 20, No. 1, 3–18

The Identification of Factors Contributing to Self-Reported Anomalies in Civil Aviation

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The main objective of this study was to analyze anomalies voluntarily reported by pilots in civil aviation sector and identify factors leading to such anomalies. Experimental data were obtained from the NASA aviation safety reporting system (ASRS) database. These data contained a range of text records spanning 30 years of civilian aviation, both commercial (airline operations) and general aviation (private aircraft). Narrative data as well as categorical data were used. The associations between incident contributing factors and self-reported anomalies were investigated using data mining and correspondence analysis. The results revealed that a broadly defined human factors category and weather conditions were the main contributors to self-reported civil aviation anomalies. New associations between identified factors and reported anomaly conditions were also reported.

self-reported anomalies civil aviation human factors pilot error text mining correspondence analysis

1. INTRODUCTION

Airline operations are very complex due to the intricate interactions between aircraft, pilots, maintenance personnel, air traffic controllers as well as seemingly more random variables such as weather, passengers, and the mental states of all those involved. The opportunities for errors, mishaps, and accidents are vast, with a multitude of potential causal factors. However, these problems also present opportunities for self-correcting actions, both human and machine in nature. Pilot errors have been previously reported to account for over 50% of incidents and accidents in most accident databases [1]. Over 70% of the incidents in the NASA aviation safety reporting system (ASRS) database were reported as caused by "human error" or, specifically, "pilot error" [2]. It is very tempting for investigators to use the blanket statement "pilot error" to attribute a cause to aircraft incidents as it encompasses many conditions while still offering the illusion of explanatory power. However, the term "pilot error" on its own does not contribute to the understanding of causal factors. More importantly, calling the cause "pilot error" does very little to help manage the conditions leading to the flight anomalies or incidents.

Although recent advancements in pilot training, hardware improvements, and regulations led to a noticeable decrease in the aviation accident rate over the past 30 years [3], managing the available sheer volume of aviation data being created is still an important issue. There is also a significant amount of "noise", which may mask key elements of data that allow conclusions about causality. Modern methods of data mining and visualizing have become very useful in meeting a challenge of information overload in general, as the amount of data being generated in the 21st century limits its usability to draw inferences. It is estimated that every year one exabyte of data, mostly digital in nature, is generated by human society. This trend

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means that, during a study period between 2002 and 2005, more data were generated than had been in all of prior human history [4].

2. HUMAN ERRORS IN AVIATION

2.1. Human Error Management

Understanding human errors can be useful in predicting and quantifying aviation safety performance. According to Reason, many systems operate for long periods with inherent safety flaws present within them [5]. These latent flaws are not revealed until an accident or incident occurs. Sträter claims that stakeholders may even know and tolerate some system flaws because of the following two states:

1. Nothing happened so far in my system => it is safe,
2. My system is safe => nothing will happen in my system [6].

Statement 2 is a simple reversion of inference from statement 1; however, this state may not actually be achieved. The appropriate way to consider either of the two statements is “There are unsafe elements in my system”. Identifying and managing the above “unsafe elements”, in most cases prevents incidents and leads to increased safety and higher performance, as the system no longer has to recover from unsafe conditions. Baker, Qiang, Rebok, et al., who investigated longitudinal trends among 558 U.S. air carrier mishaps, corroborated these findings [7]. The study revealed a 71% reduction in poor decisions being made while the airplane was underway between 1998 and 2002. However, the proportion of mishaps resulting from pilot error remained at 25%. Baker et al. stressed that the overall mishap rate remained stable, only those mishaps involving poor decisions (pilot error) decreased over the study period.

Human performance models of pilot behavior can also be tailored to individual tasks to increase their predictive capabilities [8]. Dismukes considered pilot omissions of procedural steps to be a form of prospective memory error [9]. Understanding mechanics of prospective memory errors and the conditions that are associated with them, allow designers and regulators to create procedures and designs that preclude these causal factors from existing. For example, Fischer and Orasanu found that the hierarchy within the cockpit influenced team behavior, with captains more likely to command when requesting actions of subordinates, while first officers hinted rather than directly stated their expectations of desired behavior [10]. This imbalance in communication strategies may cause errors when the check and balance system afforded by two team members is now effectively null because of the subordinate crew member’s reluctance to use stronger language or challenge a superior’s decision or action.

To aid in classifying, identifying, and mitigating the types of errors encountered in civil and military aviation, Wiegmann and Shappell created the human factors analysis and classification system (HFACS) [3]. The resulting taxonomy incorporates latent and active failures as well as preconditions and unsafe acts in an effort to cover all eventualities of error and outcome types. Li, Harris, and Yu employed HFACS to analyze 41 civil aviation accidents to describe the relationships between elements within HFACS using empirical data [11]. The findings corroborated the HFACS model assumption that active failures were exacerbated by the presence of latent failures within the organization perpetrating the errors. Furthermore, significant operational decisions made at the upper management level “trickled down” and led directly to unsafe supervisory practices. These unsafe supervisory practices were shown to contribute to unsafe pre-existing conditions that impaired pilot performance and increased possibility of accidents occurring. O’Hare employed a taxonomic approach in accident analysis to develop a framework for heuristic, investigative, and integrative functions of accident analysis and consideration of latent conditions and related human factors [12].

2.2. Precursor Analysis and Taxonomies

Other methods such as a precursor analysis have revealed novel findings on aviation investigation of accidents. The rationale for precursor analysis is that studying accident conditions yields insights about the accident itself. Phimister, Bier, and Kunreuther documented many benefits of precursor analysis [13]. Accidents are seemingly rare when viewed in light of the many safe flights completed every day. Aircraft anomalous events, however, are far more numerous. The causal factors contributing to these anomalies are not widely understood, though the conditions surrounding anomalies are often identical to those surrounding accidents. Surveying the more plentiful anomaly data will yield valuable insights as to what factors contribute to the occurrence of aircraft anomalous events. Understanding these factors can lead to improved management of such factors and, in turn, provide additional information into how to decrease the rate of accidents. For example, Liang, Lin, Hwang, et al. proposed a method for preventing error during aircraft maintenance [14]. Using Swain and Guttmann's concept of performance shaping factors (PSFs), a plan for preventing maintenance errors was created [15]. Frequencies of PSFs were linked to maintenance errors committed, and those PSFs with the highest frequencies were targeted for process improvement. Aircraft maintenance has been identified as an increasingly larger contributor to aviation incidents and, as airlines cut budgets and streamline operations, maintenance errors will continue to play a larger role. Gramopadhye and Drury provide an excellent review of trends and future work in the aviation maintenance domain [16].

Other methods of analyzing incident causes involve classifying and clustering such causes. The goal of this activity is to identify emerging patterns between similar categories. Benefits of further describing and developing the "umbrella" label of human error have been demonstrated by studies that create taxonomies of causes. The elements of the taxonomy can be further developed, described, or linked to management methods to create a powerful exploratory and explanatory device [1, 17]. Stanton and Salmon applied human error taxonomies to driving and revealed the psychological mechanisms involved in driving tasks [18]. This organization of psychological mechanisms and their supporting role in task performance allowed investigators to focus upon incidents where operators failed to perform a given task.

Finally, it should be noted that taxonomies are powerful when data-driven. For example, English and Branaghan derived a taxonomy of pilot errors based on aviation violations [19]. The taxonomy classified violations by the intent on behalf of the pilot. The four categories revealed the reasons for such violations. The violation categories comprised a desire to improve, a desire to cause harm or damage, an intent resulting from lethargy or laziness, and finally a violation stemming from a need for excitement. These four help explain psychological rationale for violations, leading to possible interventions such as training, awareness on behalf of pilots, and process improvement to stem boredom and monotony.

2.3. Aviation System Errors

Meaningful associations between errors and contributing factors can be made once appropriate categories exist for the data under analysis. Hobbs and Williamson demonstrated accident models based on contributing factors founded in the domain of aviation aircraft maintenance [20]. Their approach linked specific errors to underlying contributing factors. The errors that occur in maintenance can be truly latent and may manifest themselves after much time has passed since the maintenance error occurred or only during specific conditions. In a demonstration of the maintenance error decision aid (MEDA) process, Rankin, Hibit, Allen, et al. stressed that maintenance errors were not made intentionally by maintenance personnel [21]. If errors are not intentional, there are likely factors contributing to such errors. The MEDA process concentrates less on blaming and punishing individuals (the legacy method for alleviating maintenance error) and more on revealing causes that can be "designed out" of the maintenance process.

Wenner and Drury identified human error patterns in ground incidents [22]. Ground incidents are costly to airlines, and usually easily preventable. The authors found 12 hazard patterns comprising nine major latent failures. The relationships between the latent failures and hazard patterns were investigated and classified according to systems categories using the SHEL model [23] as well as by latent failure types. Sixty-six percent of latent failures were associated with specific hazard patterns, offering an avenue to suggest improvements to policies, staffing, or equipment to reduce ground incidents.

Predictive models of error can also offer design solutions. Stanton, Salmon, Harris, et al. tested a method for predicting pilot error based on their novel human error template framework [24]. Their framework was validated against other human error identification approaches with the overall goal being to enhance error prediction sensitivity. The creation of predictive error models can shed light on the source of error, and provide opportunities for error rate reduction through training or redesign of hardware. Traditional statistical analysis can also provide predictive power to models of error. McFadden applied logistic regression to predict pilot error [25]. The expected causes of youth and inexperience were significant contributors, but employer type (major airline or small regional airline) was also a factor. In addition, female pilots appeared to have a greater likelihood for committing an error than their male counterparts.

Another avenue of investigating factors contributing to anomalies in flight is that of trust. Automation has replaced many pilot hands-on and attention-intensive activities. The pilot has relationships with that automation just as with other pilots, air traffic control, and maintenance personnel. There is a multitude of case studies outlining over-reliance or complacency with automation, citing causes ranging from design issues to human error. Johnson, Shea, and Holloway investigated the relationship between pilots and *global positioning system* (GPS) navigation equipment [26]. They found a disturbing trend of overreliance on these devices, with expectations that the GPS system will report faults and that the data used by these devices are failsafe. The unsafe operation as well as seemingly total trust of these systems by pilots has been identified as a contributing factor in a range of accidents found within the study.

3. OBJECTIVES

One of the challenges of aviation research is that evidence and causes of human errors are not immediately apparent and are often qualitative in nature. The tendency to categorize various underlying causes under the general umbrella of human error does little to alter the rate of incident and accident reduction, as it has no explanatory power in determining causes. Furthermore, a greater understanding of errors even limited to relationships between error types affords management and intervention activities, both passive and active. This is because errors are not completely random, and are not decoupled from conditions related to their occurrence. This property means they are classifiable and can have various management methods [27]. Finally, quantifying the highly variable pilot actions is very challenging as there are no reference standards generally applicable or an all-encompassing approach.

In view of the aforementioned discussion, a new approach is required to investigate the complexity of factors contributing to aviation incidents. This paper describes a novel method of analyzing a large aviation incident database. The main objective of this study was to investigate anomalies voluntarily reported using pilots' data in the civil aviation sector in the USA to identify factors leading to those anomalies.

4. METHODS AND PROCEDURES

4.1. Methods

Experimental data were obtained from the NASA ASRS [2]. This data set contained a range of records spanning 30 years of civilian aviation, both commercial (airline operations) and general aviation (private aircraft). Narrative data as well as categorical data were used. Data were first preprocessed and divided into intelligible groups for input into relevant software packages. Factors contributing to anomalies were defined using the existing taxonomy of factors defined by the ASRS database. Similarly, the types of anomalies associated with these factors were defined by the existing taxonomy within the ASRS database structure.

The associations between specific factors and self-reported anomalies were investigated using correspondence analysis and data mining. Correspondence analysis is a descriptive technique that reveals associations between categorical data elements. SPSS r17 was used to perform the correspondence analysis. The text-mining was carried out using IBM SPSS Modeler 13: Text Analytics[1]. This software tool analyzes all available text in the data and identifies the most often encountered words, which were defined as "concepts". These concepts were filtered and grouped by types. The ASRS database used encoded words, which complicated the analysis. For example, words such as "hyd" (hydraulics) or "flt cntrls" (flight controls) were grouped into an "aircraft components" type. These types were used to identify and create rules for classifying text entries; the container element that contained these rules and types was called a "category". A list of ASRS anomaly types and subsets follows:

Air Traffic Controller Issues
Airborne Conflict
Aircraft
Aircraft Equipment
Airspace Violations
Bird/Animal
Controlled Flight Toward/Into Terrain
Clearance
Conflict
Critical
Deviation—Altitude
Deviation—Speed
Deviation—Track/Heading Deviation—Procedural
Federal Aviation Regulation
Flight Deck/Cabin/Aircraft Event
Foreign Object Debris
Fuel Issue
Gear Up Landing
Ground Conflict
Ground Event/Encounter
Ground Excursion
Ground Incursion
Ground Strike—Aircraft
Hazardous Material Violation
Illness
In-flight Event/Encounter
Landing Without Clearance
Less Severe
Loss of Aircraft Control
Maintenance
Minimum Equipment List
Near Midair Collisions
Passenger Electronic Device
Passenger Misconduct
Person/Animal/Bird
Published Material/Policy
Ramp
Runway
Security
Smoke/Fire/Fumes/Odor
Taxiway
Unsterilized Approach
Vehicle
Visual Flight Rules in Instrument Meteorological Conditions (flight into low-visibility conditions without proper authorization)
Wake Vortex Encounter
Weather/Turbulence
Weight and Balance

No Specific Anomaly Occurred
Other

4.2. Procedures

The ASRS database identified factors that were reported along with each anomaly. A total of 127 776 text records associated with anomalies available as of March 15, 2010, were used. Figures 1a–1b illustrate a typical ASRS record. The ASRS database classifies anomalies based on the types and subsets shown in section 4.1. The categorical breakdown of these anomalies and their associated factors was first conducted. The original ASRS database was organized by records, each with individual reports that contained a unique identifier code. Each record identifier contained multiple rows of data. The relevant rows of data had to be separated from the master ALL_ITEMS file, and then recombined in a new file to create additional columns, ensuring that the ITEM_ID field

[1] http://www-01.ibm.com/software/analytics/spss/products/modeler/downloads.html

was used as a key to maintain integrity of the record. The IBM SPSS Modeler 13 was used for this part of the process.

The ASRS database assessment fields identified elements as “Contributing Factors/Situations”, with a special emphasis on “Primary Problems”:

Air Traffic Controller Equipment/Navigation Facility
Aircraft
Airport
Airspace Structure
Chart or Publication
Company Policy
Environment—Nonweather
Equipment/Tooling
Human Factors
Incorrect/Not Installed
Logbook Entry
Manuals
Minimum Equipment List
Procedure
Staffing
Weather
Ambiguous

Once types for selected popular concepts were defined, these types were used to build rules to automate record classification. As shown in Table 1, these rules used logical operators to create relationships that selected and classified certain records. For example, records that contain concepts such as “hydraulic failure” or “smoke” or “burning smell” likely indicate aircraft issues or malfunctions. The selection and classification rules were created using keywords and data from the HFACS classification system [3], Boeing MEDA tool [28], and general pilot knowledge keywords elicited from a flight training text [29].

5. RESULTS

5.1. Self-Reported Anomalies

The IBM SPSS Modeler 13 was used to analyze ASRS text records associated with self-reported anomalies. Table 2 shows the concept categories extracted from these records. The most common category was the one containing concepts related

ACN: 868116 (1 of 43)

Time / Day
Date : 201001
Local Time Of Day : 0001-0600

Place
Locale Reference.ATC Facility : ZZZ.TRACON
State Reference : US
Altitude.MSL.Single Value : 10000

Environment
Flight Conditions : IMC
Weather Elements / Visibility : Icing
Light : Daylight

Aircraft
Reference : X
ATC / Advisory.TRACON : ZZZ
Aircraft Operator : Air Carrier
Make Model Name : PC-12
Crew Size.Number Of Crew : 2
Flight Plan : IFR
Mission : Passenger
Flight Phase : Descent
Airspace.Class E : ZZZ

Component
Aircraft Component : Cockpit Window
Aircraft Reference : X
Problem : Failed

Person : 1
Reference : 1
Location Of Person.Aircraft : X
Location In Aircraft : Flight Deck
Function.Flight Crew : Pilot Flying
Function.Flight Crew : Captain
Qualification.Flight Crew : Commercial
ASRS Report Number.Accession Number : 868116
Human Factors : Training / Qualification
Human Factors : Distraction
Human Factors : Human-Machine Interface

Person : 2
Reference : 2
Location Of Person.Aircraft : X
Location In Aircraft : Flight Deck
Reporter Organization : Air Carrier
Function.Flight Crew : Pilot Not Flying
Function.Flight Crew : First Officer
Qualification.Flight Crew : Commercial
ASRS Report Number.Accession Number : 868117
Human Factors : Human-Machine Interface
Human Factors : Distraction
Human Factors : Training / Qualification

Events
Anomaly.Aircraft Equipment Problem : Critical
Anomaly.Inflight Event / Encounter : Object
Detector.Person : Flight Crew
Were Passengers Involved In Event : N
When Detected : In-flight
Result.General : Declared Emergency
Result.General : Maintenance Action
Result.General : Police / Security Involved
Result.Flight Crew : Overcame Equipment Problem
Result.Aircraft : Aircraft Damaged

Assessments
Contributing Factors / Situations : Weather
Contributing Factors / Situations : Human Factors
Contributing Factors / Situations : Aircraft
Primary Problem : Aircraft

Figure 1a. Example of typical aviation safety reporting system (ASRS) record: part A.

Narrative: 1

On descent, leveling off at 10,000 feet there was a loud thunk/crack sound. The left hand windscreen was instantly spider webbed with cracks emanating from a central impact point in the lower left center, spreading to all sides of the screen. I immediately disconnected the autopilot and began to slow and level the aircraft. After resuming manual control of the aircraft, I transferred control of the aircraft to the First Officer, using a positive exchange of flight controls. Once established, I donned my oxygen mask as a precautionary measure affording me both oxygen in the event of depressurization and additional physical protection for my face. I also zipped up my **jacket** and lowered my seat. When I had accomplished these tasks, I resumed flying the aircraft by hand, and asked the First Officer to make a PA to the passengers, stating that we had sustained damage to the windscreen, there was no need to don their oxygen masks and we would be making a normal descent and landing. I then declared an emergency. I requested a lower altitude and notified them we would be slowing to a slower airspeed. They repeated the restriction of 10,000 Ft and promised lower soon, speed was our discretion. During the descent the First Officer and I discussed contingency plans if the screen were to fail (as it was continuing to crack), primarily focusing on the fact that he would take control of the aircraft and make the landing. We closed the curtain partially to remove the damage from passenger view and partially to provide protection to the cabin occupants in the event of total structural failure of the glass/plastic. We also notified operations, requesting they advise dispatch and notify maintenance. The remainder of the descent was conducted via normal procedures at a reduced airspeed. When we were unable to acquire the airport visually, we were climbed to 2200 FT and cleared for the ILS. We landed without further incident and taxied into parking, followed by both airport operations and fire/rescue as per their procedures (we did not request additional services upon landing). Upon closer inspection of the damage on the ground it appears as though the outer layer of the windscreen cracked, but no moisture or damage penetrated to the inner layer. No loss of pressurization occurred. No passenger injury or damage to persons/property on the ground occurred to our knowledge. No residue of a bird, nor additional damage was found during a thorough post flight of the aircraft. Due to lack of remains/residue, I suspect ice or foreign object rather than a bird.

Synopsis

When the outer pane of the Captain's windshield on their PC-12 shattered the flight crew declared an emergency and landed at their destination airport.

Date : 200902
Local Time Of Day : 0601-1200

Place

Locale Reference.Airport : MIA.Airport
State Reference : FL
Relative Position.Distance.Nautical Miles : 0
Altitude.AGL.Single Value : 0

Person

Reference : 1
Location Of Person : Company
Reporter Organization : Air Carrier
Qualification.Flight Attendant : Current
ASRS Report Number.Accession Number : 823441

Events

Anomaly.Other
Detector.Person : Other Person
Result.General : None Reported / Taken

Assessments

Contributing Factors / Situations : Human Factors
Contributing Factors / Situations : Environment - Non Weather Related
Primary Problem : Ambiguous

Narrative: 1

In December 2008, I had my uniform pants and a navy blue vest and 2 white shirts to be dry-cleaned. In January, when I returned from my vacation to pick-up my uniform, I gave the clerk the two pink receipts, but the clerk only returned my shirts and informed me that the pants and the vest were returned and discarded the receipts. I advised him that was not possible, but just to be sure I returned home to check my closet, my car trunk and any other location that my uniform could be, but for the last 15 years that I do business with them my dry-cleaned uniform is picked up on the return of my working trips. The owner of the establishment did show me that the pants and the vest were retrieved on the same day according to the computer entries that he did check out to me, so it's his word against my word and the thing that is not normal in this situation is that to pick up any order without the pink receipt I have to sign a release book. Today my pants, tomorrow could be my **jacket** and soon someone could have an entire uniform...please someone could you call this establishment to check this situation? I truly believe that this is not an isolated occurrence.

Synopsis

Cabin Attendant discovers that uniform pants and vest left at dry cleaners were picked up, according to the owner, but not by the Reporter.

Figure 1b. Example of typical aviation safety reporting system (ASRS) record: part B.

TABLE 1. Examples of Categories, Classification Rules (CR), Their Types and Descriptors

Category	Descriptor, Type	CR
Aircraft issues	vibration	unknown
	low oil pressure	CR
	light	unknown
	leak	CR
	hydraulic failure, inspection, disconnect, valve	CR
Knowledge-based errors		
Perceptual errors	spatial disorientation, illusion, visual perception	CR
	not heard, misjudge and disoriented	CR
Rule-based errors	wrong response, preflight, low fuel	CR
	retrospect	unknown
	exceeded ability	CR
	(misdiagnose, wrong, inappropriate, bad) and (emergency, maneuver, decision)	CR
	(bad, wrong) and (planning, preflight, fuel management go around)	CR
Skill-based errors	stalled, spin	CR
	overcompensate, over-speed, wrong direction	CR
	inadvertently	CR
	forgot, pressed wrong, pushed wrong	CR
	did not notice	CR
	bad and (technique, control, visual scan, conditions)	CR
	omitted and (step, checklist)	CR
Unsafe conditions	wake turbulence	unknown
	unsafe	CR
	self-medicating	CR
	reaction time, visual limitation	CR
	not ready	CR
	misinterpreted, misinterpretation	CR
	incapable, inaptitude, insufficient aptitude	CR
	illness, incapacitated, fatigue, fatigued	CR
	excessive and (physical, training)	CR
	conflict	CR
	attention, complacency, distraction, situational awareness	unknown
	mental fatigue, get home	CR
	(violation, violated) and (crew rest, rest, sleep, communicate, briefing, resources, leadership)	nonroutine behaviors
Unsafe supervision	unqualified	CR
	oversight	CR
	no training	CR
	known problem	CR
	hurrying	CR
	failed to enforce, unqualified, unauthorized	CR
	authorized hazard	CR
Violations	VFR into IMC, not current, not qualified, low altitude flight, unauthorized, hazardous maneuver, aggressive maneuver	CR
	follow and (procedure, directive, instruction, command, briefing)	CR
	exceeded and limits	CR
	canyon, low altitude, over-speed	
Weather	twilight	CR
	haze	unknown

Notes. VFR = visual flight rules, IMC = instrument meteorological conditions.

to unsafe conditions, followed by the rule-based errors, then skill-based errors, and knowledge based errors. Approximately 22% of the records were not categorized by the text mining algorithm, meaning they did not contain any of the keywords sought out by the algorithm.

5.2. Contributing Factors

Tables 3–4 show the total number of entries by reported anomalies and contributing factors reported for those anomalies. These anomalies were selected due to their high occurrence rates; anomalies with under 3% occurrence rates were not considered in the analysis. Procedural deviations were the most often self-reported anomalies. It should be noted that the "other" anomaly type was omitted as they were records containing non-standardized, noncategorized entries, and did not contribute any meaningful information to this analysis. In addition, Table 5 displays the contributing factors data, indicating human factors issues as being the most often reported contributors to aviation anomalies. It should be noted that the ASRS began tracking human factors category data in June 2009. This reduced dataset containing human factors category data contains 8817 records (see Table 5). These records were analyzed separately to gain additional insights about these data. The identified categories showed that troubleshooting

TABLE 2. Concept Categories Extracted From Aviation Safety Reporting System (ASRS) Text Data

Concept	No. of Records	%
Unsafe conditions	50625	39.60
Rule-based errors	33161	26.00
Uncategorized	27855	21.80
Skill-based errors	25073	19.60
Weather	21818	17.10
Knowledge-based errors	19054	14.90
Aircraft issues	10110	7.90
Violations	5287	4.10
Unsafe supervision	271	0.20
Perceptual errors	55	0.01
total	127766	100

TABLE 3. Anomaly Types and Frequencies Selected for Analysis

Anomaly Type	Frequency	%
Deviation—procedural	56087	43.9
Aircraft equipment problem	27359	21.4
Conflict	16537	12.9
In-flight event/encounter	9676	7.6
Deviation—altitude	8434	6.6
Deviation—track/heading	5294	4.1
Air traffic controller issue	4384	3.4
total	127771	100

TABLE 4. Main Factors Associated With Reported Anomalies

Factor Type	Frequency	%
Human factors	72607	56.8
Aircraft	27674	21.7
Weather	4818	3.8
Company policy	4715	3.7
Airport	3757	2.9
Ambiguous	3112	2.4
Chart or publication	2484	1.9
Procedure	2246	1.8
Environment—nonweather	2046	1.6
Airspace structure	1902	1.5
ATC equipment/navigation facility	992	0.5
Logbook entry	608	0.5
Incorrect/not installed	370	0.3
Manuals	325	0.3
Staffing	54	<0.01
Equipment/tooling	33	<0.01
Minimum equipment list	28	<0.01
total	127771	100

Notes. ATC = air traffic controller.

TABLE 5. Classification of Human Factors Category of Reported Anomalies

Category	Frequency	%
Troubleshooting	3459	39.2
Time pressure	2487	28.2
Communication breakdown	760	8.6
Situational awareness	730	8.3
Workload	386	4.4
Training/qualification	350	4.0
Other/unknown	207	2.3
Human–machine interface	190	2.2
Confusion	124	1.4
Distraction	70	0.8
Physiological—other	32	0.4
Fatigue	22	0.2
total	8817	100

aircraft equipment and time pressure were the most common contributors to aircraft anomalies for the study period. Surprisingly, fatigue, distraction, and confusion were not prominently categorized as main contributors to aircraft anomalies. Figure 2 shows the frequencies of anomalies in the human factors dataset. The most frequent anomaly types were procedural deviations and aircraft equipment problems. In light of these frequencies, the high counts of troubleshooting, and time pressure as human factors contributors to anomalies appear to follow logically.

5.3. Relationships Between Contributing Factors and Anomalies

Consistent with the methods defined by Clausen [30] and applied by Hobbs and Williamson [20], correspondence analysis was carried out with SPSS r17. Figure 3 shows the results of the correspondence analysis for self-reported anomalies and contributing factors. Items appearing close to each other denote higher degrees of association and imply a relationship. The categories appearing closer together on the plot are more closely associated than those further apart. The correspondence plot in Figure 3 shows how closely associated individual factors are based on their χ^2 distances. Nonweather related environmental issues and weather were most disassociated from the other factor types. Procedural factors, human factors issues, procedural issues, equipment and navigation facility issues, and airspace structure were all highly associated. Logbook entry problems, unclear manuals, issues pertaining master equipment list, equipment/tooling problems, and installation problems were all closely associated, as these are maintenance-related factors. Aircraft issues were slightly disassociated from the maintenance factors group, but still showed signs of association with these factors.

The value of the findings of correspondence analysis was not limited to identifying known associations between anomalies and factors. The findings also described a powerful visualization of correlations and associations. Concepts that were intuitively related and supported by data such as aircraft equipment problems and aircraft issues were displayed in close proximity to each other, as might have been expected. All of the human decision and procedural anomalies and factors were also clustered together. Seemingly random events beyond the control of the flight crew such as weather issues or nonweather environmental problems displayed a distant relationship from the other related anomaly and factor

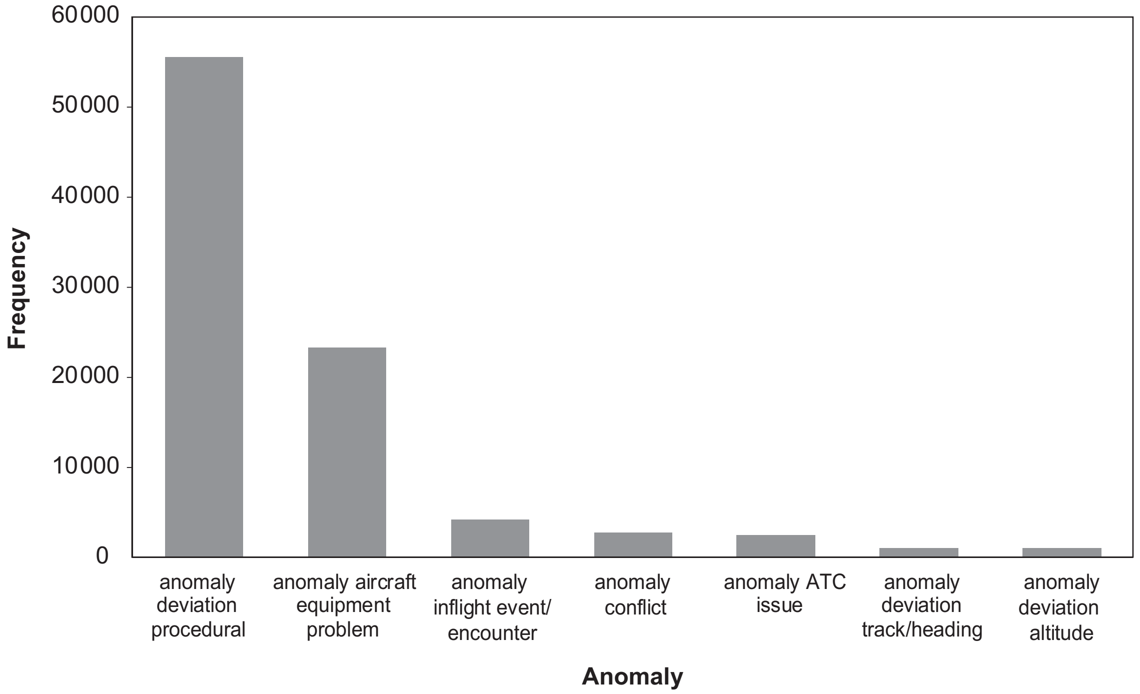

Figure 2. Anomaly types associated with the human factors dataset. *Notes.* ATC = air traffic controller.

types. Hobbs and Williamson have already used this method successfully in linking contributing factors to maintenance errors [31].

5.4. Skill–Rule–Knowledge (SRK) Taxonomy of Self-Reported Anomalies

The goal of data mining was to link latent and active factors that may contribute to self-reported anomalies. The classification of these factors was based on Wiegmann and Shappell's HFACS framework [1]. When certain keywords were found in records by the data mining software, they were linked to a corresponding category (latent or active factor). By applying this directed, "supervised" approach, web of associations between records was created. The PASW Modeler 13 Text Analytics feature was used to construct document webs examining strengths of associations of categories within records.

Figures 4–6 depict the three human error types linked to SRK taxonomy originally defined by Rasmussen [32] and then further developed by Reason [33], and the associated latent and active factors. These are illustrated using the web diagrams [34]. The associations indicate that one latent or active factor occurs in the presence of another. Bolder lines denote stronger associations, defined by a number of reports that contained both elements. Skill-based error types (Figure 4) were associated within anomaly reports along with rule-based errors as well as unsafe conditions. There was a weaker association with weather as well as a tenuous association with violations. Rule-based error types (Figure 5) were found alongside skill-based errors to have a high association with unsafe conditions. There were weak associations with perceptual errors and violations. Rule-based error types also shared some association with weather conditions and knowledge-based errors in anomaly reports. Skill- and rule-based web categories were also associated with each other, and less so with knowledge-based categories. This is supported by Reason's suggestion that skill- and rule-based errors are similar in that they share a control mode that does not exist for knowledge-based errors [33].

The knowledge-based web (Figure 6) suggests that knowledge-based errors occurred when the pilot was facing unfamiliar or unknown circumstances. These were also strongly associated with unsafe conditions, and less so with weather and violations. Such association supports feedback theories of knowledge-based errors, where the

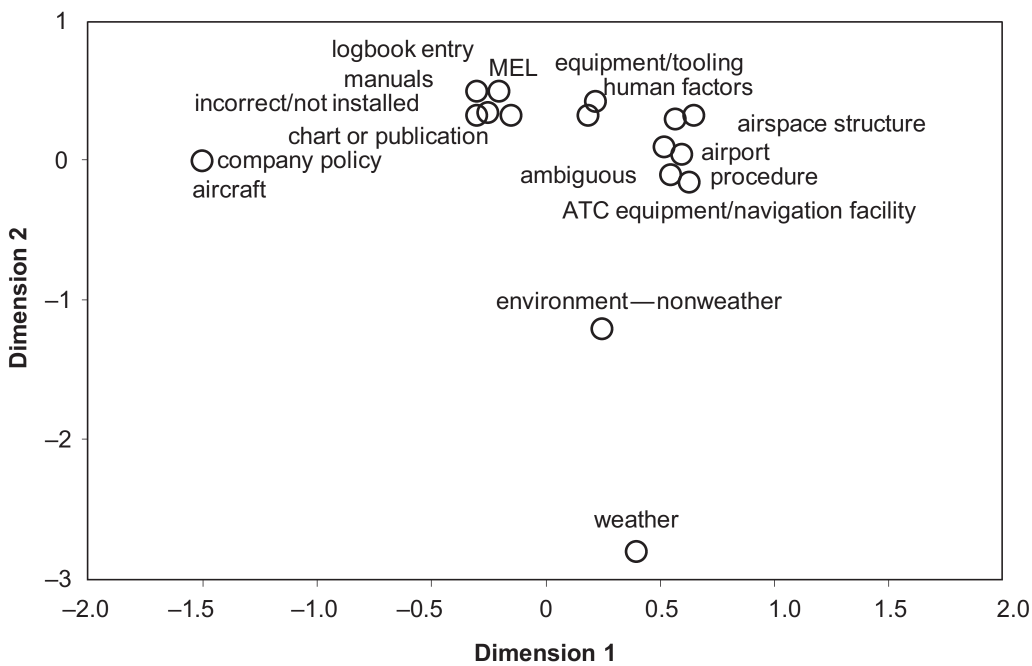

Figure 3. Correspondence analysis plot for analyzed anomalies. *Notes.* MEL = minimum equipment list, ATC = air traffic controller.

individual encountering the error must employ slower, more intensive cognitive processing to solve the problem [33]. It is highly likely that these errors would be encountered in situations where equipment troubleshooting activities were also present. Knowledge-based error types appeared to be weakly associated with perceptual errors and violations, and there were strong associations with unsafe conditions types, rule-based errors, and skill-based errors. Finally, knowledge-based error types had some association with weather conditions as well.

6. DISCUSSION

The results of this study extend the existing knowledge on aviation anomalies, with the premise that the conditions surrounding these anomalies may also be present when a real incident occurs. Most contributing factors attributed to self-reported aviation anomalies were classified as human factors. However, it was also shown that aircraft hardware contributed to 20% the anomalies reported in the sampled ASRS data. It is very likely that the troubleshooting actions taken by the flight crew were reported as human factors. This suggests a need for more training of pilots to be more consistent in the categorization and documentation of flight anomalies allowing the reported data to capture relevant casual factors.

The most prevalent category found across all self-reported anomalies was the "unsafe conditions" category. Rule-based error categories were found more frequently than skill- or knowledge-based error categories. This contradicts past aircraft accident studies [3], whether civilian or military, that employed the HFACS system and found skill-based errors to be most prevalent. However, the present study investigated anomalies containing conditions similar to the conditions exhibited in actual incidents. Furthermore, perceptual errors were also not identified as frequently in the present study they were in previously reported studies.

Another interesting difference uncovered by the present study is that only 4% of the examined ASRS records were identified as having elements that would constitute a violation. Wiegmann and Shappell found that ~25% of aviation accidents contained some sort of violation [3]. It is conceivable that, despite the assurances to pilots that their information is confidential and not traceable, many pilots are still hesitant to report their own violation activities. However, the low occurrence of unsafe supervision identified in the present

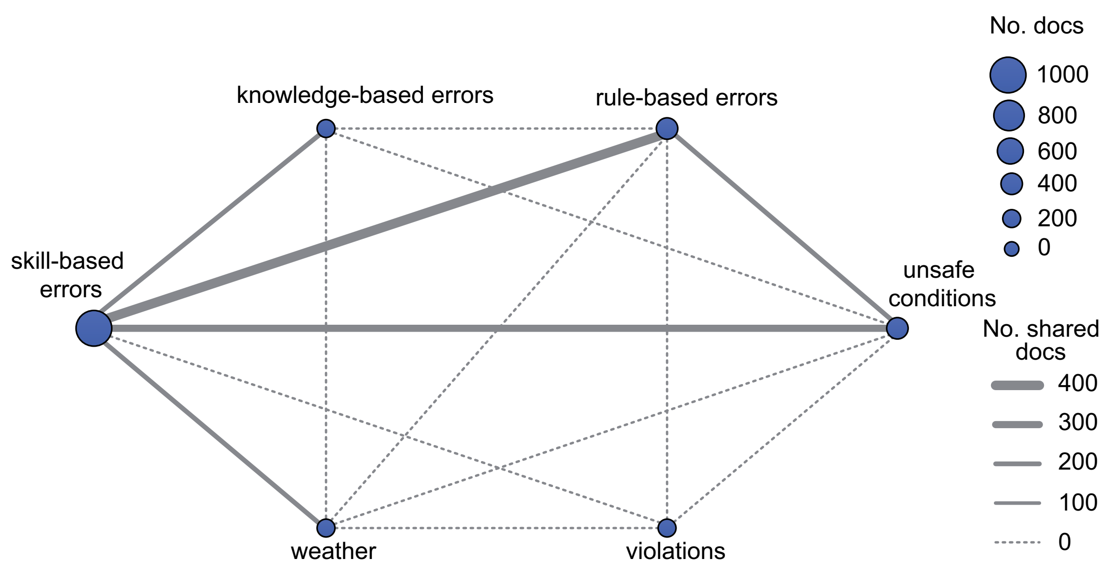

Figure 4. Associations between latent and active factors contributing to reported anomalies under skilled-based errors category web.

study is consistent with Wiegmann and Shappell [3], who also found low percentages of unsafe supervision in aviation accidents. Identifying unsafe supervision is difficult, as assigning blame to an entire organization rather than an individual has much larger consequences for aviation-related operations, especially if serious violations or oversights are found. This may indicate a weakness in aviation (and likely other) incident data collecting processes where human actions are often blamed for the mishap, but never credited for recovery.

7. CONCLUSIONS

This study limited the data sources to a single large repository, i.e., the NASA ASRS. This repository contained only voluntary reports submitted

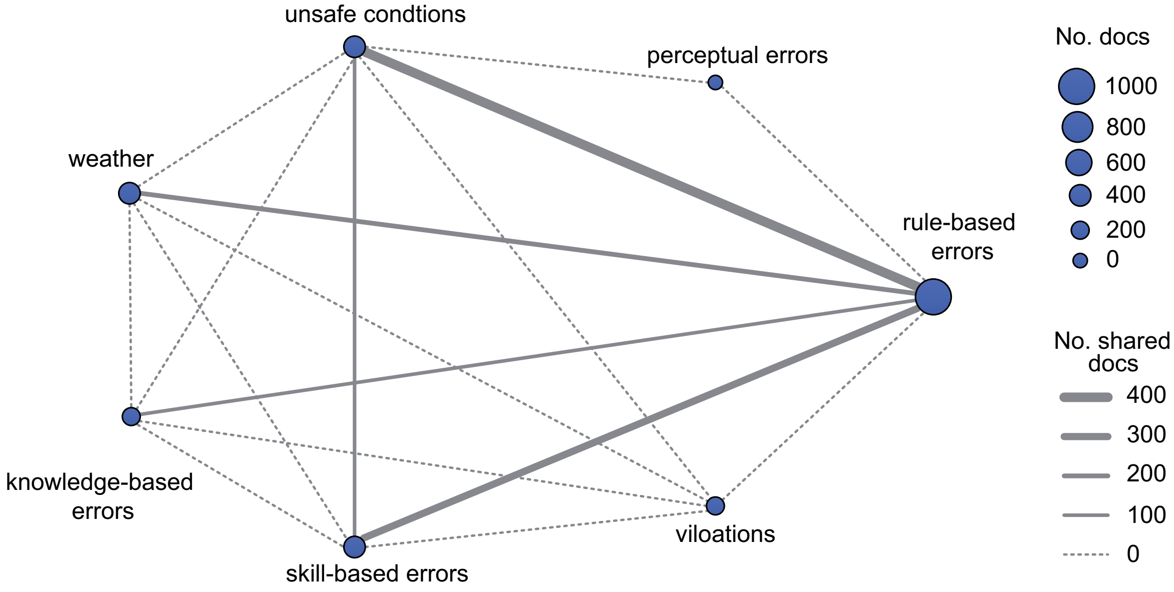

Figure 5. Associations between latent and active factors contributing to reported anomalies under rule-based errors category web.

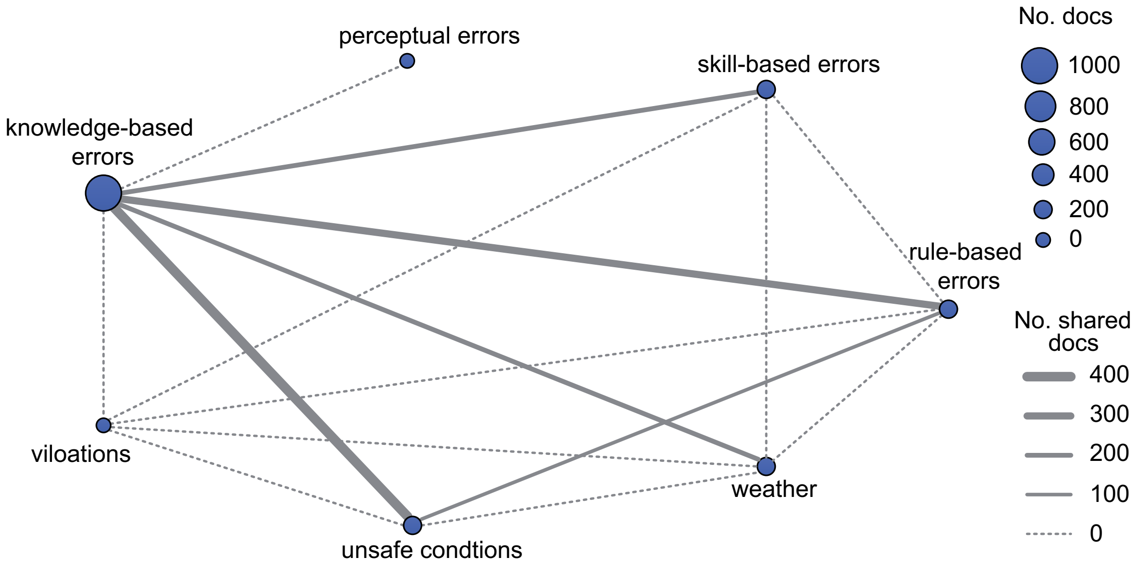

Figure 6. Associations between latent and active factors contributing to reported anomalies under knowledge-based errors category web.

by pilots flying both private and commercial operations. No military data were included in this dataset. The encoded nature of the ASRS database, with its many abbreviations, eliminated the possibility of a context-link analysis using a traditional dictionary. The data would have to be decoded; this was deemed unfeasible due to the number of encoded terms. In addition, much of aviation terminology is rife with acronyms, abbreviations, and nonstandard technical terms. A context analysis, though very powerful, is usually limited to full-text sources such as web pages and interview or survey data.

To provide the widest breadth of data for this study, all available anomaly data were analyzed. The data were not partitioned by any means such as by date, type of operation, or type of aircraft. It is possible and very likely that there are underlying patterns within sections of the data. Anomaly types and frequencies for large airline operations, e.g., will be different than they are for student pilots or recreational flights. These types of underlying patterns were not discovered. Future studies might investigate whether anomaly types and frequencies changed over time, as this was deemed beyond the scope of this study.

Furthermore, to reduce the effect of noise in the data only the top seven most frequently occurring anomalies were studied. The other anomaly data were discarded, even though there could have been additional insights or categorizations based on these additional anomaly types. The findings of this study also corroborate psychological constructs of error patterns and their underlying mechanisms. Greater understanding of these mechanisms bring practical applications of new and exciting fields such as cognitive engineering and ergonomics contributing to design processes and streamlining existing practices. Finally, the predictive models can serve to drive new training exercises focusing on reducing or eliminating those dangerous situations such as those where knowledge is scarce and slow feedback processing is required prior to actions being taken. Although the possibility of achieving a perfect safety record and zero accident rates for the aviation industry is highly unlikely, it is important to identify causal factors to reduce the accident rate as much as possible to accommodate the drastic increase in worldwide air travel traffic. Only through collaboration across disciplines and integration of meaningful findings can powerful, self-correcting, and sustainable safe practices emerge that will guide the aviation field into its exciting future.

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