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Associations between Errors and Contributing Factors in Aircraft Maintenance

Alan Hobbs, Australian Transport Safety Bureau, Canberra, Australia, and Ann Williamson, Injury Risk Management Research Centre, Sydney, Australia

In recent years cognitive error models have provided insights into the unsafe acts that lead to many accidents in safety-critical environments. Most models of accident causation are based on the notion that human errors occur in the context of contributing factors. However, there is a lack of published information on possible links between specific errors and contributing factors. A total of 619 safety occurrences involving aircraft maintenance were reported using a self-completed questionnaire. Of these occurrences, 96% were related to the actions of maintenance personnel. The types of errors that were involved, and the contributing factors associated with those actions, were determined. Each type of error was associated with a particular set of contributing factors and with specific occurrence outcomes. Among the associations were links between memory lapses and fatigue and between rule violations and time pressure. Potential applications of this research include assisting with the design of accident prevention strategies, the estimation of human error probabilities, and the monitoring of organizational safety performance.
occur. A variety of generic cognitive taxonomies have been used to account for errors in safety-critical environments (see Senders & Moray, 1991).

**Reason’s Model of Unsafe Acts**

In recent years, the model of unsafe acts proposed by Reason (1990) has become one of the most widely used generic cognitive error models. Reason’s (1990) model, which is a development of his earlier generic error modeling system (GEMS; Reason, 1987), draws on the skill-rule-knowledge (SRK) distinction of Rasmussen (1983) and the slip/mistake dichotomy of Norman (1981), but it also includes rule violations as a distinct form of unsafe act. Violations have not always been included in error taxonomies, even though they are a significant problem in safety-critical industries (Lawton, 1998; Mason, 1997). According to Reason (1990), skill-based, or unintended, unsafe acts take the form of slips and lapses, whereas unsafe acts involving intended actions can take the form of rule-based or knowledge-based mistakes and of violations. A particular strength of Reason’s (1990) model is that it apparently “cuts nature at the joints” or at least segments errors into categories consistent with current models of human information processing.

Although error theorists such as Rasmussen (1983) and Reason (1990) have not aimed to explain skill development, their taxonomies clearly capture important distinctions between levels of cognitive control as a person deals with progressively more familiar and predictable situations (Anderson, 1982; Fitts & Posner, 1967). The distinction between skill-based errors and mistakes involving intended actions is also consistent with the automatic/controlled distinction of Shiffrin and Schneider (1977), with skill- and knowledge-based errors relating to automatic and controlled processing, respectively. Rule-based errors are associated with controlled processing lying between the extremes of skill- and knowledge-based performance. Such behavior fits well with the concept of scripts or schemata (Bartlett, 1932), in which the person possesses a previously developed solution that can be applied in familiar situations. Additionally, the identification of violations as a distinct form of error has been supported by studies of driver behavior (Aberg & Rimmoe, 1998; Parker, Reason, Manstead, & Stradling, 1995).

Reason’s (1990) taxonomy has been used extensively in the analysis of accident case studies (e.g., Lucas, 1997; Maurino, Reason, Johnston, & Lee, 1995) and has been adapted for use in several accident investigation models, including Tripod Beta (Shell International Exploration & Production B.V., 1994), incident cause analysis method (ICAM; Hayward, Lowe, & Gibb, 2002), and the human factors analysis and classification system (HFACS) of Shappell and Wiegmann (2000). Nevertheless, very few published studies have applied Reason’s (1990) taxonomy to errors drawn from occurrence databases. This is despite the advantages that aggregated occurrence data can provide in revealing patterns and associations that would not be apparent from case studies alone. In one of the few such studies, Wiegmann and Shappell (2001) applied an error model based on that of Reason (1990) to a sample of airline accidents. They found that skill-based errors were most prevalent, followed by mistaken decisions (either rule based or knowledge based) and violations.

**Error-Producing Conditions**

Formal models of accident causation and operational investigation systems are both generally based on the notion that errors are not random events but, rather, occur in response to causal factors (Heinrich, 1941; Reason, 1990). In the literature one can find a great range of potential error factors relating to virtually every aspect of human performance in technological systems (Hawkins, 1993; International Civil Aviation Organization, 1995).

Aircraft maintenance is performed in an environment that contains many potential error-producing conditions. Maintenance workers routinely contend with inadequately designed documentation, time pressures, shift work, and environmental extremes (International Civil Aviation Organization, 1995). Hobbs and Williamson (1995) conducted critical incident interviews with airline maintenance personnel and found that error factors included not only technical problems, such as poor procedures and inadequate trade knowledge, but also nontechnical issues, such as time pressure, communication...
breakdowns, inadequate supervision, and the physical environment. Additional information on the human factors influencing airline maintenance was obtained by Predmore and Werner (1997), who asked senior airline mechanics to identify the challenges of their jobs. The most common answers concerned dealing with people and time pressures.

Several investigation methodologies have been developed for aviation maintenance incidents. The oldest and most widely used of these, Boeing’s maintenance error decision aid (MEDA), presents a comprehensive list of error phenotypes, such as “access panel not closed,” and then guides the investigator in identifying the contributing factors that led to the error. More than 70 contributing factors are listed, including fatigue, inadequate knowledge, and time constraints (Rankin & Allen, 1996). In common with MEDA, the aircraft dispatch and maintenance safety (ADAMS) system includes a range of maintenance error phenotypes but also enables the investigator to identify a large number of potential error genotypes, such as habit capture and memory failure. The investigator is provided with a choice of approximately 100 performance-influencing factors covering the task, the work environment, the organization, and the error-maker’s physical and mental state (Russell, Bacchi, Perassi, & Cromie, 1998).

A maintenance adaptation of the HFACS methodology (Schmidt, Schmorrow, & Hardee, 1998) assists the investigator in identifying maintenance actions using a taxonomy based on that of Reason (1990) and provides 25 potential latent conditions that contribute to maintainer errors.

Despite the increasing interest in maintenance error, limited information is currently available on the cognitive forms that these errors take and the factors that promote them. A key reason for this is that unlike aircrew errors, maintenance errors can remain latent for significant periods before an accident or incident occurs, making the work of an investigator particularly difficult. Furthermore, unlike pilots or air traffic controllers, maintenance personnel are not subject to data or voice recording for investigation purposes, and investigators sometimes have a difficult job establishing the circumstances surrounding maintenance errors. Additionally, many of the existing data on maintenance error are stored in company files and are not available to the public. The lack of information on maintenance error presents an immediate problem for airlines, which in many countries are required to introduce programs to address maintenance human factors (Joint Aviation Authorities, 1998).

**Associations between Contributing Factors and Errors**

Although information on maintenance errors is scarce, errors in other industries have been studied extensively with a range of cognitive error taxonomies (e.g., O’Hare, Wiggins, Batt, & Morrison, 1994; Runciman et al., 1993; Wagenaar & Groeneweg, 1987). However, the links between errors and contributing factors have received little attention. In many studies of safety databases, errors and contributing factors are analyzed independently of each other, and their frequencies are reported in separate, unlinked tables. A major limitation of this type of research is that lessons learned in one context may not generalize to other domains. For example, identifying that skill-based errors are the most frequent errors committed by locomotive drivers (Edkins & Pollock, 1997) may not necessarily indicate what to expect in other industries. Additionally, the comprehensive lists of contributing factors found in many accident investigation frameworks, although providing useful guidance to investigators on a case-by-case basis, are less useful for database analysis. By placing factors into a large number of categories, the differences between accident cases are emphasized and similarities are obscured.

Given these limitations, we propose that it is preferable to focus on the **associations** between categories within data sets, such as those between errors and contributing factors, as this information may be more readily generalizable across domains. Such information has several important uses. Accident prevention strategies can be targeted at key factors that contribute to error, human error probabilities can be estimated with greater accuracy, and organizational safety performance can be monitored by evaluating the relative prevalence of conditions that are known to promote errors.

One of the few studies exploring the links between errors and contributing factors was...
carried out by Feyer, Williamson, and Cairns (1997), who used the SRK framework to analyze data relating to more than 1000 workplace fatalities in Australia. They identified links between particular error forms and specific pre-existing work practices within the deceased workers’ organizations. For example, they found that skill-based slips were associated with pre-existing unsafe work practices in the use of personal protective equipment. Although theirs was not strictly a study of errors and contributing factors, Salminen and Tallberg (1996) linked skill-, rule-, and knowledge-based errors with the type of work being performed at the time of serious occupational accidents in Finland and found that errors were not evenly distributed across work tasks. Skill-based errors were most common when workers were using manual tools, whereas errors on supervision tasks tended to be knowledge based.

Given the widespread use of Reason’s (1990) unsafe act model, it is somewhat surprising that no published study deals with the links between Reason’s (1990) unsafe act categories and contributing factors. The purpose of the current study was to partly rectify this situation by examining the associations between maintenance errors and the circumstances in which they occur.

Are Contributing Factors Equally Associated with All Forms of Error?

It is sometimes assumed, apparently for the sake of simplicity, that error-producing factors increase the prevalence of all errors equally. However, because errors appear to reflect a range of cognitive origins, it seems likely that specific contributing factors would be associated with particular forms of human fallibility. At the very least, it might be expected that the conditions that promote errors of automatic performance (such as slips) would be different from those that promote mistakes involving controlled processing (such as rule-based or knowledge-based errors).

For example, automatic performance can be expected to be highly reliable in a task environment that is consistent and predictable; however, tasks that involve variability between cues and required responses would be associated with less reliability in skilled performance (Fisk, Ackerman, & Schneider, 1987). According to Lawton and Parker (1998), violations are likely to be associated with contributing factors different from those that promote other unsafe acts. They noted that motivational factors, unrealistic work demands, and unworkable procedures are particularly likely to lead to rule violations. Others have considered that work and time pressures are significant precursors of violations (Battmann & Klumb, 1993).

We contend that two possibilities exist concerning the associations between errors and factors. The first is that the presence of a contributing factor will be associated with a general increase in the prevalence of all forms of error. The alternative possibility is that particular contributing factors will be associated with increases in the prevalence of specific errors, rather than an overall increase in all forms of error. In order to evaluate these possibilities, a database of aircraft maintenance occurrences was analyzed using an accident analysis system developed by Feyer and Williamson (1991), incorporating a relatively short list of preconditions designed to capture the factors that have been linked previously with maintenance errors. Maintenance errors were categorized using an error model based on that of Reason (1990). This approach enabled errors to be examined within their ecological context, maintaining intact the links between errors and contributing factors.

METHOD

Study Population

The study population consisted of approximately 4900 aircraft maintenance personnel (all those who were listed in an Australian government database as holders of maintenance licenses issued by the Civil Aviation Safety Authority of Australia) and approximately 300 unlicensed mechanics employed by major airlines in Australia.

Safety Questionnaire

A questionnaire was developed to gather information on a range of safety issues pertinent to aircraft maintenance. In addition to questions dealing with working conditions and work practices (reported elsewhere: Hobbs &
Williamson, 2000, 2002a, 2002b), respondents were given the opportunity to report a critical incident. The critical incident technique was first described by Flanagan (1954) and is now widely used in error research. The questionnaire probes are presented in the Appendix.

The questionnaire was distributed by post to the home addresses of the maintenance personnel. A reply-paid envelope was provided to enable respondents to return completed questionnaires anonymously. To encourage participation, respondents had the option of entering a lottery for five prizes, including tools, clothing, and pocketknives.

Because questionnaire responses were anonymous, respondents who wished to enter the lottery were required to invent two security codes (one of eight characters and one of four characters) and write these in spaces provided on the cover page of the questionnaire. Two months after the distribution of the survey, the winning eight-character codes were posted to all aviation mechanics. The winning respondents then claimed their rewards by telephone and confirmed their eligibility for the prize by quoting their unpublished four-character code. Respondents were not obliged to complete the survey to participate in the lottery. It was made clear to respondents that they were not required to report an occurrence and that they could leave the occurrence section of the questionnaire blank and move on to the next section of the survey if they could not recall any occurrences.

**Occurrence Analysis**

The outcome of each occurrence was coded using a descriptive taxonomy based on MEDA (Rankin & Allen, 1996). This taxonomy was used to provide a technical description of the final result of the occurrence, such as "access panel not closed" or "material left in aircraft.”

The circumstances leading up to the outcome were then analyzed using the technique developed by Feyer and Williamson (1991) to examine fatal workplace accidents. This approach permits occurrences to be broken down into a sequence of up to three events (see Figure 1). Each event was then coded into one of three categories: environmental, hardware-related, or behavioral events. *Environmental events* were defined as those that resulted from the location of the occurrence and which could not have been changed by personnel at the time – for example, a gust of wind. *Hardware-related events* were those in which a tool or component broke or malfunctioned. *Behavioral events* were further categorized using an error taxonomy based on that of Reason (1990) but with

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**Figure 1.** Schematic representation of occurrence coding system.

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the addition of two additional categories of error. The first of these, perceptual error, has been demonstrated to be an important class of error in other aviation environments (Wiegmann & Shappell, 2001) and was considered particularly relevant given the importance of visual inspection in aircraft maintenance (Drury, 1999). The category of mischance was added to the taxonomy to cover occasions in which an unsafe action nevertheless constituted “correct” behavior – for example, those in which a person accurately followed a deficient procedure (Feyer & Williamson, 1991). Definitions of errors appear in Table 1.

When appropriate, contributing factors were linked with each occurrence. The factor taxonomy used in this study was intended to capture the broad range of error-producing conditions identified in previous maintenance research, without resulting in excessively fine-grained descriptions of factors. The resulting taxonomy was based on that of Feyer and Williamson (1991) but with the addition of coordination, fatigue, and pressure. In assigning factors, care was taken to ensure that a single issue was not counted simultaneously as an event and a contributing factor. So for example, if an environmental event occurred, the environmental factor would not be used to describe the same problem. Contributing factors are defined in Table 2.

To evaluate the reliability of the coding system, 40 randomly selected occurrences analyzed by the main coder were analyzed independently by a check coder.

**Statistical Procedure**

Cross tabulations of errors and contributing factors, as well as of occurrence outcomes and errors, were created. In order to examine relationships between these categorical variables, each table was analyzed using correspondence analysis. Correspondence analysis is an exploratory procedure that converts complex data tables into a visual form that is easier to interpret (Clausen, 1998). The technique requires no assumptions about the data other than that values are not negative. For each variable, categories are represented as points in two-dimensional space based on the chi-square distances between categories. Categories that appear together on the correspondence analysis biplot have a stronger association than categories that appear apart.

For each factor, chi square was calculated to evaluate whether the prevalence of all error types changed uniformly when the factor was present in comparison with when the factor was not present. The strength of the association between contributing factors and each error was estimated using a series of logistic regression analyses; in each case, factors were entered simultaneously to predict the presence or absence of each error type. An advantage of logistic regression is that the exponent of the beta coefficient is interpretable as the odds ratio.

<table>
<thead>
<tr>
<th>Error</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceptual error</td>
<td>A failure to detect a sign that the person was attempting to detect</td>
</tr>
<tr>
<td>Memory lapse</td>
<td>The omission of an action that the person intended to perform</td>
</tr>
<tr>
<td>Slip</td>
<td>The performance of a familiar skill-based action at a time when this action</td>
</tr>
<tr>
<td></td>
<td>was not intended, or the failure to carry out such an action correctly; this</td>
</tr>
<tr>
<td></td>
<td>category included fumbles and trips</td>
</tr>
<tr>
<td>Rule-based error</td>
<td>A failure to correctly invoke familiar rules or procedures, either written</td>
</tr>
<tr>
<td></td>
<td>or based on experience, when dealing with routine problems or when making</td>
</tr>
<tr>
<td></td>
<td>decisions in familiar situations</td>
</tr>
<tr>
<td>Violation</td>
<td>An intentional deviation from procedures or good practice</td>
</tr>
<tr>
<td>Knowledge-based error</td>
<td>An error in a situation that was unfamiliar or that presented new problems</td>
</tr>
<tr>
<td></td>
<td>for the person, for which neither automatic mappings nor rules existed</td>
</tr>
<tr>
<td>Mischance</td>
<td>The person adhered to correct procedures, but his or her behavior was</td>
</tr>
<tr>
<td></td>
<td>nevertheless instrumental in leading to the occurrence</td>
</tr>
</tbody>
</table>
weight for each predictor is an odds ratio. This expresses the increase in prevalence of the error that was noted when the contributing factor was present, as opposed to when the factor was not present. Odds ratios can range from 0 to $\infty$. A value of 1 indicates that the presence of the factor was not associated with a change in the prevalence of the error. A value greater than 1 indicates the degree to which the error became more prevalent when the factor was present. A value less than 1 can be taken to indicate that the factor was not related to an increase in prevalence of the error but not necessarily that the factor provided protection against the error.

In the remaining cases, the reporters indicated that they had witnessed the event.

**Reliability of Occurrence Coding**

For the categorization of occurrences into sequences of behavioral, environmental, and hardware-related events, 90% agreement was achieved with the check coder. For contributing factors, the level of agreement was 93%. Cohen’s kappa was .67 for the coding of occurrence outcomes and .68 for the coding of errors. According to the guidelines of Landis and Koch (1977), these values of Cohen’s kappa represent a substantial level of interrater consistency.

**Nature of the Occurrences**

The outcomes of the reported occurrences are listed in Table 3. The most common occurrence outcome was a system operated unsafely during maintenance – for example, a mechanic in the cockpit activated one of the aircraft’s hydraulic systems, unaware that another mechanic was currently working on that system elsewhere on the aircraft. The next most frequent outcome was incomplete installation, in which all necessary components were present but a step in the installation process had been omitted.
Behavioral events were involved in 96% of occurrences. The most commonly identified errors were memory lapses, violations, and knowledge-based mistakes, followed by slips and rule-based mistakes (see Figure 2). Common memory lapses were forgetting to perform a task at the end of a maintenance procedure, such as not closing an access panel, or failing to restore a disturbed system to its normal state. Violations frequently took the form of decisions to omit task procedures, the use of unapproved procedures, or failures to use correct tools or equipment. Examples of error types are given in Table 4.

**Table 3: Occurrence Outcomes**

<table>
<thead>
<tr>
<th>Outcome</th>
<th>N</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>System operated unsafely during maintenance</td>
<td>80</td>
<td>13</td>
</tr>
<tr>
<td>Incomplete installation</td>
<td>48</td>
<td>8</td>
</tr>
<tr>
<td>Maintenance worker contacted hazard</td>
<td>45</td>
<td>7</td>
</tr>
<tr>
<td>Incorrect assembly or location</td>
<td>44</td>
<td>7</td>
</tr>
<tr>
<td>Towing event</td>
<td>44</td>
<td>7</td>
</tr>
<tr>
<td>Vehicle or equipment contacted aircraft</td>
<td>31</td>
<td>5</td>
</tr>
<tr>
<td>Material left in aircraft</td>
<td>27</td>
<td>4</td>
</tr>
<tr>
<td>Wrong equipment or part installed</td>
<td>23</td>
<td>4</td>
</tr>
<tr>
<td>Part not installed</td>
<td>22</td>
<td>4</td>
</tr>
<tr>
<td>Part damaged during repair</td>
<td>21</td>
<td>3</td>
</tr>
<tr>
<td>Panel or system not closed</td>
<td>21</td>
<td>3</td>
</tr>
<tr>
<td>Required service not performed</td>
<td>20</td>
<td>3</td>
</tr>
<tr>
<td>Failure of component or tool</td>
<td>15</td>
<td>2</td>
</tr>
<tr>
<td>Fault not found</td>
<td>15</td>
<td>2</td>
</tr>
<tr>
<td>Falls and trips</td>
<td>14</td>
<td>2</td>
</tr>
<tr>
<td>System not made safe before maintenance</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>System not reactivated</td>
<td>10</td>
<td>2</td>
</tr>
<tr>
<td>Pin or tie left in place</td>
<td>9</td>
<td>1</td>
</tr>
<tr>
<td>Documentation error</td>
<td>9</td>
<td>1</td>
</tr>
<tr>
<td>Other</td>
<td>95</td>
<td>15</td>
</tr>
</tbody>
</table>

Note: For an additional 14 occurrences, the outcome could not be determined.
* Figures are rounded to nearest percentage.

The Role of Contributing Factors

The most commonly coded contributing factor was pressure, which was involved in nearly one-quarter of all reported incidents, followed by equipment, training, coordination, and fatigue (see Figure 4). The environment and previous deviation factors were involved in relatively few occurrences. The physiological factor was used in only 1% of cases and has been excluded from further analysis.

Chi-square analysis indicated that with the sole exception of environment, each contributing factor was associated with increases in specific errors, not with uniform changes in the prevalence of all error types. Because multiple tests were performed, a Bonferroni correction was
**TABLE 4: Examples of Errors**

<table>
<thead>
<tr>
<th>Error Type</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceptual error</td>
<td>After being on duty for 18 hr on a long overtime shift, the worker was carrying out a general inspection on an engine at around 22:00. He missed obvious damage to the internals of the cold stream duct area. The damage was found later, when another defect was being investigated.</td>
</tr>
<tr>
<td>Memory lapse</td>
<td>Just prior to the departure of the aircraft, I remembered I had left a blanking plug within the engine inlet area. I advised the pilot that I needed to check that area again and retrieved the blank.</td>
</tr>
<tr>
<td>Slip</td>
<td>Without thinking, I moved to wipe oil with a rag. The rag was ingested in the engine intake causing FOD [Foreign Object Damage].</td>
</tr>
<tr>
<td>Rule-based error</td>
<td>A mechanic did not check the position of the flap lever before he pushed in a cockpit circuit breaker that provided electrical power to a hydraulic pump. When the pump started, the flaps began to retract automatically. This could have caused damage to the aircraft or injured other workers.</td>
</tr>
<tr>
<td>Violation</td>
<td>At the end of a shift we realized that an engine hadn’t been run to check for oil leaks when the aircraft was to be placed on line. Under pressure to avoid a delay due to this oversight, the run was carried out too quickly and the engine was not un-cowled properly to check for oil leaks and consequently after departure that particular engine ran out of oil as the result of a damaged seal.</td>
</tr>
<tr>
<td>Knowledge-based error</td>
<td>I wanted to turn the radio master on but could not find it, as the switches were poorly marked or unreadable. I was unfamiliar with the aircraft, so I asked an airframe tradesman who was working on the aircraft and he pointed to a red rocker switch. I queried him and he said that must be it. I pushed the switch and the right engine turned over, with the propeller narrowly missing a tradesman who was inspecting the engine. There is no radio master in this aircraft. I immediately marked the “start” and some other switches and learned a valuable lesson.</td>
</tr>
<tr>
<td>Mischance</td>
<td>A service procedure was carried out in accordance with the aircraft maintenance manual. The manual however, contained an error, which resulted in an aircraft system failing to operate correctly during a functional test at the end of the maintenance procedure.</td>
</tr>
</tbody>
</table>

**Figure 2.** Events involved in maintenance occurrences.
used to adjust alpha to .006. The results were as follows: fatigue, $\chi^2(6, N = 641) = 39.51$, $p < .001$; pressure, $\chi^2(6, N = 641) = 18.31$, $p = .005$; coordination, $\chi^2(6, N = 641) = 48.10$, $p < .001$; training, $\chi^2(6, N = 641) = 138.11$, $p < .001$; supervision, $\chi^2(6, N = 641) = 20.24$, $p = .005$; previous deviation, $\chi^2(6, N = 641) = 19.60$, $p = .005$; procedures, $\chi^2(6, N = 641) = 59.95$, $p < .001$; equipment, $\chi^2(6, N = 641) = 29.61$, $p < .001$; environment, $\chi^2(6, N = 641) = 11.58$, $p = .072$.

For each error, Table 5 presents the outcome of the logistic regression equation predicting the presence or absence of the error on the basis of contributing factors. In all cases, factors as a set were able to predict the presence or absence of errors at a statistically significant level. The columns in Table 5 labeled “OR” (odds ratio) present the exponent of the beta weights for each factor in relation to each error. Figure 5 (which can be referred to in conjunction with Table 5) presents the correspondence analysis plot showing the relationships between errors and factors. As can be seen in Figure 5, the following associations between error types and contributing factors emerged:

1. The most common error type, memory lapse, was associated with pressure, fatigue, and the environment factor. Table 5 indicates that when fatigue was listed as a factor, the odds of a memory lapse were 2.4 times higher than when fatigue was not a factor. Fatigue, however, was not associated with an increase in the prevalence of violations, rule-based errors, or knowledge-based errors.

2. Rule-based error and mischance clustered with procedures, coordination, and previous deviations. As can be seen in Table 5, procedure problems were associated with a ninefold increase in the odds of a mischance.

3. Knowledge-based errors showed a strong association with training. Training issues were associated with an approximate 12-fold increase in the odds of a knowledge-based error.

4. Slips were most closely related to equipment deficiencies, although the environment factor and fatigue also clustered nearby.

5. Violations were most closely associated with pressure.

DISCUSSION

The great majority of the reported incidents were wholly or partly a result of the behavior of maintenance personnel. The most frequent error
was a lapse in which a person forgot to perform an intended action, an event widely referred to as a *prospective memory failure* (Brandimonte, Einstein, & McDaniel, 1996). Four other types of error were also particularly important. These were violations, slips, knowledge-based errors, and rule-based errors. In most cases, particular contributing factors were associated with an increased incidence of particular errors rather than with an overall increase in all forms of error. Although some of the associations (notably between training and knowledge-based errors and between procedures and mishance) would be expected by definition, in other cases the current findings represent new information concerning the ecological context of errors in safety-critical settings.

Skill-, rule-, and knowledge-based errors were each associated with different clusters of factors. Some of the factors that were associated with the skill-based errors of slips, lapses, and perception errors could be considered local or transitory in nature (fatigue, pressure, and the environment). Knowledge- and rule-based errors, however, were linked with training and procedures, respectively, factors that may represent longstanding organizational issues. If, as Reason (1990) suggested, errors can reflect latent organizational failures, the current findings raise the possibility that errors of controlled processing could have deeper organizational roots than do errors of automatic performance.

Of particular note was the finding that fatigue was associated with failures to carry out intentions (such as memory lapses and perceptual errors) but was not associated with knowledge-based or rule-based errors. Given that fatigue is a major issue of concern in industry (Moore-Ede, 1993), this result lends support to the views of de Vries-Griever and Meijman (1987), Monk and Folkard (1983), and others who maintain that fatigue is more likely to interfere with automatic processing than with controlled processing.

McDonald, Corrigan, Daly, and Cromie (2000) found that 34% of routine maintenance tasks at airlines were performed contrary to procedures. The most common reasons given for such violations were that there was an easier or quicker way than the formal procedures or that the procedure was unclear. The current results appear to be at variance with these findings, as reporters did not tend to mention procedural problems when explaining why violations occurred. A possible explanation is that each study gathered a different subset of violations. The participants in the study of McDonald et al. were going about their normal tasks and were not involved in maintenance incidents. It is possible that they were reporting what Lawton

**Figure 4.** Factors contributing to maintenance occurrences.
### TABLE 5: Strength of Associations between Factors and Errors, Expressed as Frequencies and as Odds Ratios (OR) Derived from Logistic Regression

<table>
<thead>
<tr>
<th>Factor</th>
<th>Perceptual Error</th>
<th>Memory Lapse</th>
<th>Slip</th>
<th>Violation</th>
<th>Rule-Based Error</th>
<th>Knowledge-Based Error</th>
<th>Mischance</th>
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<tr>
<td></td>
<td>n</td>
<td>OR</td>
<td>n</td>
<td>OR</td>
<td>n</td>
<td>OR</td>
<td>n</td>
</tr>
<tr>
<td>Fatigue</td>
<td>13</td>
<td>3.2**</td>
<td>33</td>
<td>2.4**</td>
<td>16</td>
<td>1.4</td>
<td>11</td>
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<tr>
<td>Pressure</td>
<td>9</td>
<td>0.6</td>
<td>52</td>
<td>1.7*</td>
<td>23</td>
<td>0.7</td>
<td>43</td>
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<tr>
<td>Coordination</td>
<td>5</td>
<td>0.8</td>
<td>13</td>
<td>0.6</td>
<td>3</td>
<td>0.2</td>
<td>12</td>
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<tr>
<td>Training</td>
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<td>7</td>
<td>0.3</td>
<td>7</td>
<td>0.5</td>
<td>8</td>
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<tr>
<td>Supervision</td>
<td>3</td>
<td>0.6</td>
<td>11</td>
<td>0.7</td>
<td>8</td>
<td>0.8</td>
<td>16</td>
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<tr>
<td>Procedure</td>
<td>11</td>
<td>2.5*</td>
<td>15</td>
<td>0.9</td>
<td>3</td>
<td>0.2</td>
<td>12</td>
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<tr>
<td>Equipment</td>
<td>4</td>
<td>0.5</td>
<td>9</td>
<td>0.3</td>
<td>27</td>
<td>2.0**</td>
<td>27</td>
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<tr>
<td>Previous deviation</td>
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<td>0.4</td>
<td>0</td>
<td>0.0</td>
<td>5</td>
<td>1.0</td>
<td>4</td>
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<tr>
<td>Environment</td>
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<td>3.0*</td>
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<td>1.5</td>
<td>8</td>
<td>1.2</td>
<td>9</td>
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Overall Fit of Logistic Regression Model to Predict Error

<table>
<thead>
<tr>
<th>$\chi^2$ (9, N = 805)</th>
<th>25.21</th>
<th>63.63</th>
<th>40.92</th>
<th>22.68</th>
<th>38.63</th>
<th>120.55</th>
<th>46.68</th>
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<tbody>
<tr>
<td>$p$</td>
<td>&lt;.003</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
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</tbody>
</table>

* Wald test significant at $p < .05$, ** Wald test significant at $p < .01$. 
(1998) referred to as “routine” violations. In contrast, the safety occurrences described in this study may have been more likely to include “exceptional” violations – rare actions that occur in unusual situations.

The design of the current study does not permit causal inferences to be drawn from the patterns of errors, factors, and outcomes. Nevertheless, the associations among contributing factors, particular errors, and outcomes suggest several targets for intervention. For example, the close relationship between knowledge-based errors and parts damaged during repair suggests that a useful way to reduce this outcome would be to target knowledge-based errors and the conditions that promote them – most notably, inadequate training and supervision.

More generally, the specific links between errors and contributing factors provide guidance for managers seeking to reduce the incidence of human error in maintenance or in other noncontinuous control tasks. As a general rule, it appears that human error reduction strategies would be best tailored to specific errors and their particular contributing factors rather than to human error in general. Several possible interventions can be proposed on the basis of the findings.

Rule-based errors could be addressed by improvements in coordination between workers, such as through maintenance team training (Taylor & Christensen, 1998). Attention to the management of worker fatigue and production pressures may help to reduce the incidence of memory lapses, the most common form of maintenance error. Similarly, violations could be addressed by better management of situational factors such as production pressures and equipment deficiencies. Although it is highly unlikely that factors such as fatigue or pressure can be entirely eliminated from the workplace, it may be appropriate to train workers in strategies to cope with time pressures and to ensure that shift rosters are designed in such a way that fatigue is kept within reasonable limits.

The associations between contributing factors and particular errors also have the potential to assist with the prediction of human reliability. For example, fatigued personnel can be expected to be at particular risk of memory lapses, and a job environment in which workers are denied correct or properly functioning equipment.
might be expected to increase the odds of slips and violations.

It should be noted that although odds ratios are widely used to estimate relative risk, particularly in medicine, they should be interpreted with caution and can be misleading if interpreted as a precise measure of risk, rather than as a general indicator of the magnitude by which risk has increased (Davies, Crombie, & Tavokoli, 1998). Unlike probabilities, odds do not have an upper bound and are not linear expressions of risk. For example, doubling the odds of an event from 2:1 to 4:1 does not double the chances of the event but, rather, increases the probability from .66 to .80.

All field studies of safety occurrences suffer to a greater or lesser extent from the possibility that the data reflect biases such as recall and motivational influences (Safren & Chapanis, 1960). Several potential biases could have affected the current study. First, respondents may have been unaware of some of the circumstances surrounding the occurrence they described, or they may have filtered or elaborated their responses on the basis of preconceived notions concerning errors and their causes. Nevertheless, data provided by workers should not necessarily be seen as less accurate than information gathered by expert accident investigators. It could be argued that the workers themselves are likely to have insights into the nature of their job that would not be available to outsiders.

A second potential problem is that those who responded may have been unrepresentative of the total population of maintenance personnel or that the incidents they reported may have been atypical. Almost three quarters of the surveys were not returned, and of those that were, less than half contained occurrence reports. The anonymity provided to encourage reporting makes it difficult to evaluate the representaiveness of the sample. However, one piece of evidence suggesting that the reports are generally representative of aircraft maintenance incidents is that the pattern of errors and contributing factors are broadly consistent with findings from previous studies (although this could be because previous studies were influenced by the same biases). The omission of an intended action, the most frequently reported error in the current study, was also the most frequent maintenance error found in a sample of airline maintenance incidents by Reason (1997). The most common contributing factor, time pressure, was also identified as the most common contributing factor in maintenance reports received by the Aviation Safety Reporting System (2002).

An additional limitation of the current study is that it was based on reports of work discrepancies, yet no information was available on the occasions when tasks were completed without incident. It is possible that aircraft maintainers routinely perform their assigned tasks in the face of challenges such as fatigue or time pressure. Observations of pilot behavior during routine flights have helped to put in context the behavior of cockpit crews during abnormal situations (Helmreich, Wilhelm, Klinect, & Merritt, 2001). Such an approach may also be useful on the hangar floor, where evaluating the level of error-producing conditions during normal maintenance tasks could help to establish more clearly their role in error production. An additional question for future research is whether the associations found between errors and contributing factors would be apparent in other maintenance-occurrence databases or, indeed, in safety data from other industries. Ultimately, laboratory tasks may provide the best opportunity to control the presence or absence of error-producing conditions and to examine the relationships between errors and contributing factors.

In conclusion, the current study has suggested that important relationships exist between errors and contributing factors. Although a common response to workplace errors and violations has been to “blame and train” the individuals concerned, the current findings suggest that the particular circumstances in which errors occur should be a key target for safety interventions.

APPENDIX

Probe Questions

Safety incidents happen in all professions, including aircraft maintenance. Such incidents can help us to identify areas where improvements can be made. We are interested in your experience of safety incidents. Please tell us about a maintenance incident which involved you or someone else. A maintenance incident can be anything which could have prevented...
an aircraft from operating normally or could have put the safety of a worker at risk. (If you cannot recall any incidents, go on to [next section of the survey].)

[Reporters were required to indicate that they had either witnessed or participated in the events they described. Background information associated with each occurrence – as such as the time of day, the type of aircraft involved, and whether an official report had been filed – was collected with the aid of multiple-choice or restricted-response questions and is not reported here.]

1. What happened?
   Most incidents involve a chain of events. Start with the first thing that happened and then describe each of the things that happened next. Try to give as much detail as you can. If people played a part in the incident, tell us whether they were a LAME [Licensed Aircraft Maintenance Engineer], AME [unlicensed Aircraft Maintenance Engineer] or an apprentice, but please do not identify anyone.

2. Why do you think the incident happened?
3. Was there anything about the way things are done at your company which contributed to the incident (for example, something about the equipment, documentation, procedures etc.)?
4. Did the incident occur because of something you or another person did, or didn’t do?
   __Yes → __Another person ___Myself
   __No (go on to [remaining restricted response questions])

Please describe the most important thing that you or they did wrong (or didn’t do).

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REFERENCES


Alan Hobbs is a senior research associate at San Jose State University Foundation/NASA Ames Research Center. He received a Ph.D. in psychology from the University of New South Wales in 2001.

Ann Williamson is the executive director of the Injury Risk Management Research Centre, Sydney, Australia. She received a Ph.D. in psychology from La Trobe University in 1979.

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