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Using a Data-Driven Method of Accident Analysis: A Case Study of the Human Performance Reliability (HPR) Process

A.W. Armstrong, William R. Brokaw[‡], Randy Block
Kestrel Management, LLC
Madison, WI 53713

[‡]Presenter E-mail: wbrokaw@kestrelmanagement.com

Abstract

Human error and its contribution to occupational accidents and incidents has received considerable research attention in recent years. However, more research is needed into the validity, practicality, and functionality of using data-driven accident/incident analysis methods to identify factors that contribute to incidents with the greatest frequency. This paper presents a case-study of one such method: Human Performance Reliability (HPR). **Methods:** The authors conducted approximately 30 HPR reviews to analyze incidents that occurred at a large refining company over a three year period. Through the HPR process, the authors identified the most common human errors, other contributing factors, and the controls (SOPs, processes, programs) that failed to prevent the accidents/incidents. **Results:** A Chi-Square Goodness-of-Fit test and post-hoc analysis of Standard Residuals on the human error frequencies revealed the most common human errors and contributing factors, while raw frequency counts showed the most commonly associated controls (see Tables 3-6). The Chi-Square statistic was $X^2 = 528.58$, indicating that certain errors were contributing to incidents significantly more often than others. **Discussion:** Early evidence supports the notion that the HPR process is an effective tool for incident analysis and subsequent continuous improvement efforts in process safety.

Introduction

The concept of human error and its contribution to occupational accidents and incidents has received considerable research attention in recent years. As mechanical systems become safer and more reliable, human error is more frequently being identified as the root cause of or a contributing factor to an incident (Health and Safety Executive, 1999). When an accident/incident occurs, investigation and analysis of the human error that led to the incident reveals vulnerabilities in an organization's management system.

This concept is illustrated by James Reason's well-known "Swiss Cheese" model of incident causation (see Figure 1). Unfortunately, most organizations have a finite number of resources (financial, time, and knowledge) that can be used to address the identified vulnerabilities. That makes the ability to identify the *most frequent* human errors and the *most problematic* controls (e.g., SOPs, safety programs, PPE) very valuable. Being able to do so allows an organization to focus its limited resources on the corrective action(s) that are most likely to have the biggest impact on the organization's incident rate.

This paper describes one method for identifying the most frequent human errors and most problematic controls, and presents a case study wherein the method was applied to a large petroleum refining company.

Human Error

While research related to human error in occupational settings has accelerated in recent years, the concept was already being explored almost a century ago. In 1919, Greenwood and Woods introduced research demonstrating that certain individuals were more accident-prone than others. In other words, Greenwood and Woods (1919) posited that accident-proneness is an immutable personality characteristic as stable and reliable as, for example, extraversion or conscientiousness. Their conclusions were embraced by industry for decades, and common practice throughout this time was to terminate employees involved in accidents (since they were deemed accident-prone) rather than acknowledging and addressing system flaws (e.g. poorly written procedures, lack of engineered controls, poor management and supervisory practices) that made human error likely or even inevitable (Armitage, 2009).

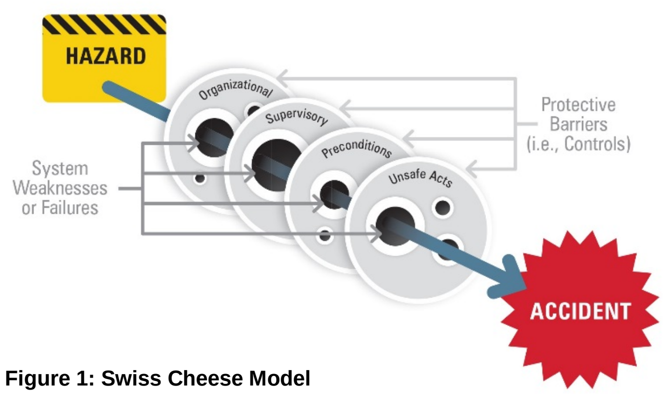


Figure 1: Swiss Cheese Model

The concept of accident-proneness as a personality trait was challenged in 1974 when James Reason tried and failed to replicate the findings of Greenwood and Woods (Armitage, 2009). As a result, Reason began to theorize that incident occurrence was due to a combination of internal personality factors and external environmental circumstances (Reason, 1974; Armitage, 2009). Reason's failure to replicate Greenwood and Woods' results was confirmed by Lawton and Parker (1998), who also pointed out that Greenwood and Woods' reliance on very old and very young research subjects may have contributed to their anomalous results. The paradigm shift resulting from Reason's findings in 1974 gradually made examining the system factors after an incident more popular and blaming the worker involved in the incident less commonplace.

During the early 1970s, models of human error began to focus more on cognitive factors, including the inherent limitations of human ability. It was during this era that Rasmussen and Jensen (1974) proposed a model of human error that divided human performance into three separate levels: skill-based, rule-based, and knowledge-based.

- Skill-based tasks are those that require pre-packaged, clearly applicable actions (Rasmussen & Jensen, 1974; Armitage, 2009).
- Rule-based tasks differ from skill-based in that the entire action is not pre-packaged, but general heuristics apply that can make the task easier and more efficient.
- Knowledge-based tasks are completely novel situations in which the individual must uncover a solution or best course of action without the benefit of prior experience—accordingly, they are the most susceptible to human error (Rasmussen & Jensen, 1974; Armitage, 2009).

The primary utility of this model is the ability to determine potential novel situations that would require knowledge-based solutions, then train workers in the proper course of action so that the task becomes rule- or skill-based. An example would be conducting emergency drills so workers know the proper response if and when a true emergency happens.

Contrary to Rasmussen and Jensen's model of human error, Norman (1988) focused on the characteristics of the error itself rather than the task. According to Norman (1988), there are three types of human errors: slips, lapses, and mistakes. All three of these error types would later be described by Reason as 'active errors' (Reason, 1997).

- A mistake is characterized by an improper judgment in selecting either the objective itself or the process of fulfilling the objective (Armitage, 2009).
- Lapses are typically memory failures where the individual fails to remember to perform a complete action or portions of that action (Armitage, 2009; Norman, 1988).
- Slips are execution errors, where the individual fails to carry out the action as planned (Armitage, 2009).

Very often, slips involve a failure due to automation, whereby the individual is so familiar with a task that he/she does not pay close enough attention to its execution and makes an error (Armitage, 2009). For that reason, experts are more likely to experience slips, while inexperienced individuals are more likely to experience lapses and mistakes (Armitage, 2009). Other common types of slips include description errors, associated activation errors, and loss of activation errors (Armitage, 2009).

The discussion of human error up to this point has focused only on true errors: an individual intends to do the right thing but fails to do so. Or, as Reason defines it, "the failure of a planned action to be completed as intended—without the intervention of some unforeseeable event; or the use of a wrong plan to achieve an aim" (Reason, 1990, p.9). Another category of actions—violations—are often included in discussions of human error, even though some have argued that they are not errors. According to Armitage (2009), a violation represents a deliberate or intentional deviation from rules or standard operating procedures. Violations may result from cognitive factors, personal motives (Ajzen, 1991), or organizational motives (Reason, Parker, & Lawton, 2001), but any negative consequences that result from the violation are almost always unintended (Parker & Lawton, 2003).

Violations are typically subcategorized into routine, situational, or exceptional violations (Health & Safety Executive, 1999).

- Routine violations are deliberate deviations from the rules that are done continuously due to lack of enforcement from supervisors and/or management, desire to save time, and/or the individual's perception that existing rules are too restrictive (Health & Safety Executive, 1999).

- Situational violations involve deliberate deviations that are strongly encouraged/reinforced by environmental conditions, such as operational pressure, insufficient staff, or inappropriate physical design of the workplace (Health & Safety Executive, 1999).
- Exceptional violations are large deviations from standard procedures done in unusual circumstances, such as in a crisis situation (Health & Safety Executive, 1999).

Some have argued that the above conceptualizations are overly simplistic. For example, Perrow (1984) has argued that complex systems, such as refineries or chemical plants, facilitate organizational accidents by virtue of their complexity. Also, Dekker (2006) has argued that the Swiss Cheese model, in particular, is too simplistic and conceptualizes incidents as linear/sequential, rather than dynamic, interdependent, and complex. Additionally, the above conceptualizations of error have focused mainly on the operator level, and mostly ignore the contributions of supervisory factors and organizational influences—what Reason might call latent conditions (Health and Safety Executive, n.d.). Finally, with the modern emphasis on 'big data', the above conceptualizations of error are of limited practical utility when analyzing incidents or human error, in general, for common trends and patterns.

Two types of processes have arisen in response to the need for practical data analysis related to human error: (1) Human Reliability Analysis (HRA) methods and (2) more robust models of accident/incident investigation.

Human Reliability Analysis (HRA) Methods

HRA methods are risk assessment tools designed to determine the relative probability that a human error will occur during a certain process (Cuschieri & Tang, 2010). The final probability assessment is affected by many factors, including the quality of the equipment/machinery in the process, the human/machine interface, and the temporary and stable characteristics of the process operator (Cuschieri & Tang, 2010). Cuschieri and Tang (2010) propose that HRA methods fall into three categories: subjective, probabilistic HRA; depend HRA; and HRA based on cognitive control theory. Kim and Bishu (2006) also proposed three broad categories, but identified them as task-based analysis, response time-based analysis, and expert knowledge-based analysis (see Table 1 for definitions of all these concepts).

Some of the most common examples of HRA will be briefly described below. Potential limitations of these HRA methods is that they are time-consuming, require extensive expertise, and do not offer guidance on which processes to select for review. Many large organizations with PSM-covered processes have thousands of processes and procedures and limited resources to conduct detailed process analysis like HRA. Therefore, the ability to identify the most problematic procedures and processes for which HRA should be conducted would be valuable to these organizations.

Technique for Human Error Rate Prediction (THERP)

The Technique for Human Error Rate Prediction (THERP) was first developed for the nuclear power industry by Swain & Gutman in the 1960s (Swain & Guttmann, 1983). The steps involved in THERP are as follows:

"(1) Define the system failures of interest. These pertain to system functions that may be influenced by human errors and for which error probabilities are to be estimated.
(2) List and analyze the related human operations. […]
(3) Estimate the relevant error probabilities.
(4) Estimate the effects of human errors on the system failure events. This step usually involves integration of the HRA with a system reliability analysis.
(5) Recommend changes to the system and recalculate the system failure probabilities" (Swain & Guttman, 1983, p. 5-3).

Table 1: Definitions of HRA categories

Theorists	Concept	Definition
Cuschieri & Tang	Subjective, probabilistic risk assessment	Process is broken into its component parts; each part is assigned a failure probability, and probabilities are combined into an overall probability for the entire process.
Cuschieri & Tang	Depend HRA	Introduce levels of dependency between Human Factor Events (HFEs) in response to the linear, independent event framework of subjective, probabilistic HRAs.
Cuschieri & Tang	HRA based on Cognitive Control Theory	Identify three situational factors (competence, control, constructs) that heavily influence error probability.
Cuschieri & Tang*	Competence	The range of different actions that the system is capable of executing at a given time under situational conditions.
Cuschieri & Tang*	Control	The quality of organization/orderliness with which competence is applied and executed.
Cuschieri & Tang*	Constructs	Knowledge or assumptions about the situation within the system as it is taking place.
Kim & Bishu	Task-based analysis	Task is broken into subtasks; subtask error probabilities are found and combined into an overall process probability.
Kim & Bishu	Response time-based analysis	Focuses on whether an operator can realistically complete a task in a pre-determined amount of time.
Kim & Bishu	Expert judgment-based analysis	Rates the values of the factors that are thought to influence failure and success probabilities and they are then combined into a single rating.

**As cited by Cuschieri & Tang, originally defined by Hollnagel, 2000*

THERP would be classified as a task-based analysis by Kim and Bishu (2006) and a subjective, probabilistic risk analysis by Cuschieri and Tang (2010). One limitation of THERP is that it was developed specifically for the nuclear power industry. Another is that it is complex and difficult for non-experts to use (Cuschieri & Tang, 2010). In fact, the guidance document for completing the THERP process is over 700 pages long (Swain & Guttmann, 1983). However, simpler versions have been created by the original theorists, including the Accident Sequence Evaluation Program (ASEP) and Simplified Human Error Analysis (SHEAN).

Human Error Assessment and Reduction Technique (HEART)

The Human Error Assessment and Reduction Technique (HEART) is another example of a task-based analysis method. The steps involved include the following:

(1) Categorize the process into one of nine generic categories.
(2) Identify all applicable Error Production Conditions.
(3) Evaluate the severity of the Error Producing Conditions.
(4) Combine the results of steps 1-3 into a final probability of error (Williams, 1985).

Although still somewhat difficult to use, HEART is simpler than THERP and applies to a broader cross-section of industries. However, HEART still requires experience and knowledge to use properly. Additionally, Kim & Bishu (2006) have pointed out that HEART and other HRA methods that use probability estimates are fundamentally flawed due to the unpredictable and sometimes irrational actions that humans take. Kim & Bishu (2006), therefore, recommend a fuzzy math approach to HRA that eschews precise probabilities in favor of a range of probable outcomes.

Cognitive Reliability and Error Analysis Method (CREAM)

The Cognitive Reliability and Error Analysis Method (CREAM) is an example of an HRA methodology based on the Cognitive Control Theory identified and defined by Hollnagel (2000). The primary steps involved are to:

(1) Build or develop a list of the cognitive demands of the task (see Table 2 for a list of the top cognitive demands).
(2) Identify the likely cognitive function failures.
(3) Determine the specific action failure probability.

CREAM analysis focuses primarily on creating a Failure Modes and Effects Analysis (FMEA), but with human behavior/error rather than mechanical failure.

Table 2: Cognitive Functions Used in the CREAM Methodology

Cognitive Activity	Definition
Coordinate	Bringing two or more activities or systems together to accomplish a shared objective.
Communicate	Receiving or sharing information required for task accomplishment via verbal, written, or electronic means.
Compare	Evaluating two or more entities with the intention of identifying similarities and differences between them.
Diagnose	Interpreting available information to formulate a theory regarding the cause of one or more problems.
Evaluate	Assessing a situation to determine the appropriate action(s) to take.
Execute	Carrying out a planned action.
Identify	Using existing information to create a theory regarding the nature of a particular object or situation.
Maintain	Taking necessary action(s) to keep a system at its current status.
Monitor	Continuously assessing the operational status of a system over an extended

	period of time.
Observe	Taking a single measurement of the operational status of a system.
Plan	Imagining a series of actions that, when carried out, will achieve a desired outcome.
Record	Creating a log of an event or events.
Regulate	Altering the condition(s) of a system in order to achieve an objective.
Scan	Getting a superficial overview of the system status in order to obtain a general impression.
Verify	Confirming the accuracy of the system status, whether by checking records or taking measurements/observations.

Accident/Incident Investigation

The influence of human error on accidents has been increasingly incorporated into investigation methods in recent years. While ‘Human Error’ may have been an acceptable root cause designation for an accident several decades ago, a deeper and more systematic assessment of human error has become necessary (Health and Safety Executive, 1999). This recent emphasis on human error has resulted in an expansion of knowledge related to human error and the most common human errors and other factors contributing to incidents.

For example, Ion (2011) found that the most frequent errors among aircrews that led to incidents were loss of situational awareness, violation of rules and regulations, failure to follow safe procedures, poor judgment in decision-making, preoccupation with minor mechanical problems, and inadequate leadership. Ion (2011) also found that non-technical factors significantly contributed to accidents, including cognitive skills (planning, preparation, decision-making, awareness), interpersonal skills (communication, teamwork, leadership, conflict resolution), and emotional climate/stress.

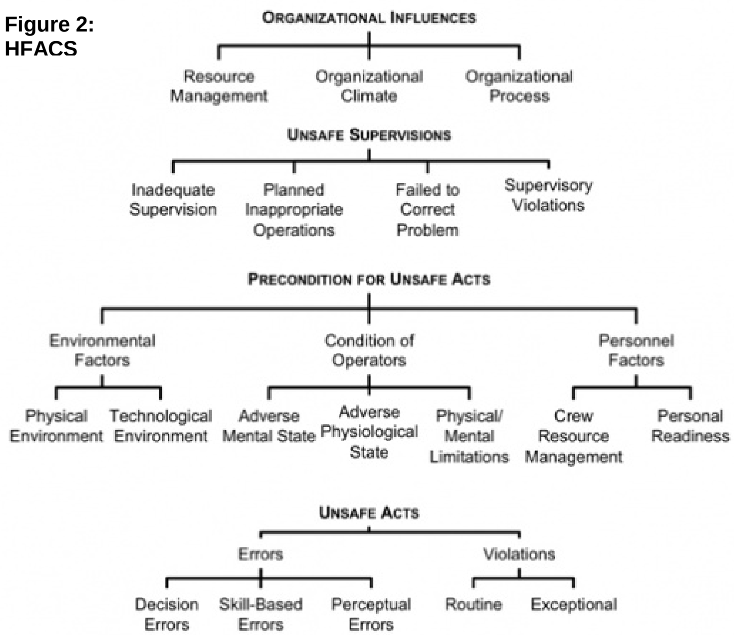
Shappell, Detwiler, Holcomb, Hackworth, Boquet, and Wiegmann (2007) also recount the results of a study in which six pilot-raters classified aircrew, supervisory, organizational, and environmental causal factors associated with 1020 commercial aviation accidents (181 air carrier aircraft and 839 commuter/on-demand aircraft) that occurred over a 13-year period to determine trends. Nearly 70% of accidents were associated with some manner of organizational, supervisory, or aircrew failure, although the percentages varied slightly when air carrier (45%) and commuter/on-demand (75%) aviation accidents were considered separately (Shappell et al., 2007). Of these, the vast majority of the accidents were associated with aircrew factors.

Multiple other researchers have also highlighted the importance of improving safety culture in reducing incidents (Cooper, 2001; Roughton & Mercurio, 2002; Mannan, Mentzer, & Zhang, 2013).

Human Factors Analysis and Classification System (HFACS)

The Human Factors Analysis and Classification System (HFACS; see Figure 2) was developed by Scott Shappell and Douglas Wiegmann in the early 2000s as an incident analysis method for the aviation industry (Wiegmann & Shappell, 2000). HFACS synthesized the various human factors that had been found to contribute to incidents and organized them into a conceptual framework. HFACS was specifically developed as a way to “define the holes in the cheese” of Reason’s Swiss Cheese model (Wiegmann & Shappell, 2000, p. 70). It also allows data from multiple incidents to be aggregated in order to look for patterns and trends in incident causation. Essentially, the model allows incident investigators to find the similarities in a group of incidents that appear dissimilar at first glance, but that have specific categories of human error in common.

Figure 2: HFACS



HFACS categorizes errors into four levels: unsafe acts, preconditions, supervisory factors, and organizational influences (Wiegmann & Shappell, 2000). Within each level, there are multiple categories that are used to classify the various factors that contributed to each incident (see Figure 2).

According to Dekker (2003), classification of human error may serve a practical purpose, as it can assist organizations in understanding and, therefore, managing human error. However, Dekker (2003) also argues that the process of classifying errors, in and of itself, does not provide deeper understanding of the incident. Additionally, a potential limitation of HFACS, specifically, is that there is no method to tie the contributing factors in an incident back to the operational procedures, processes, or programs of the individual organization. As a result, HFACS could provide a great deal of information regarding the errors that occur most frequently, but it does not guide the analyst toward the most efficient way to mitigate the risks associated with those human errors.

Human Performance Reliability (HPR)

HPR is a process developed by the author’s company that allows the analyst to associate individual controls (e.g., SOPs, programs, processes) to each human factor that contributed to an incident. HPR adapts the framework provided by HFACS (with revisions aimed at generalizing the method beyond the aviation industry) to conceptualize and classify human error and other contributing factors, but with the additional step of associating the control(s) that failed to prevent the incident from occurring. As more and more accident reviews are done, patterns and trends in the data appear showing both the human errors and the controls that are appearing most frequently in accident reviews. This process, as a data-driven method of accident/incident analysis, allows organizations to identify how and where to focus resources to drive safety performance improvements.

What follows is a case study where the HPR process was used to review the significant accidents of a petroleum refining company.

Method

The authors were provided with detailed reports of approximately 30 significant safety or environmental incidents that occurred within a three-year period at two refineries owned by the refining company in this case study. These incidents included fires, product releases, power outages, injuries, and a single fatality. The HPR reviews focused on the information provided in the incident reports, as well as the SOPs, programs, and processes provided to the authors by the refining company and the individual refineries.

The authors reviewed the incidents in accordance with the HPR process, classifying human errors that contributed to each incident and associating one or more failed controls with each identified error. In some cases, no control currently existed at the refineries to prevent the error in question. In those instances, the authors identified a control the refineries could implement to prevent similar errors in the future. For reasons of confidentiality, the specific details of the reviewed incidents cannot be reproduced in this paper. However, the errors and controls that most frequently contributed to incidents will be reviewed and discussed in the following sections.

Results

The data generated by the HPR review process are frequency counts of how often errors and controls were identified. The error frequencies were analyzed using a chi-square goodness-of-fit test and a post-hoc analysis of standard residuals for each error. The null hypothesis (i.e., that no error would contribute to incidents more frequently than others) was used to derive the theoretically expected value for the goodness-of-fit test. For each error type, the theoretically expected value was calculated by summing the total number of errors identified in that HFACS level (i.e., unsafe acts, preconditions, supervisory factors, organizational influences) and dividing by the number of questions in that level. These values were then compared to the observed error frequency. A partial contingency table illustrating this method can be found in Table 3.

Table 3: Partial Contingency Table of Human Error Identified Frequencies

Level	Quest. #	Question	E	O	O-E	$(O-E)^2$	$(O-E)^2/E$
Unsafe Acts	1	Incorrectly assess situation	3.96	14	10.04	100.74	25.42
Unsafe Acts	2	Failure to consult supervisor	3.96	7	3.04	9.22	2.33
Unsafe Acts	3	Experience or knowledge exceeded	3.96	6	2.04	4.15	1.05
Unsafe Acts	4	Unaware of changes in environment or conditions	3.96	6	2.04	4.15	1.05

Unsafe Acts	5	Failure to follow prescribed procedure	3.96	12	8.04	64.59	16.30
Unsafe Acts	6	Use wrong procedure	3.96	1	-2.96	8.78	2.22
Unsafe Acts	7	Unaware of procedure or task changes	3.96	0	-3.96	15.71	3.96
Unsafe Acts	8	Not paying attention	3.96	3	-0.96	0.93	0.23
Unsafe Acts	9	Distracted by conditions	3.96	2	-1.96	3.85	0.97

The chi-square statistic for n=125 (the number of error types) was $X^2 = 528.58$, which is significant at $\alpha = 0.01$. Standard residuals were subsequently calculated and ranked in order of magnitude. A partial list can be found in Table 4.

Table 4: Partial List of Standard Residuals, Ranked by Magnitude

Level	Quest. #	Human Factors	E	O-E	√E	SR
Preconditions	19	Leadership failure to guide	3.18	11.83	1.78	6.64
Organizational	36	Failure to identify and manage risks	4.73	13.27	2.18	6.10
Supervisory	1	Failure of oversight	6.18	14.82	2.49	5.97
Supervisory	7	Failure to recognize unsafe conditions/practices	6.18	14.82	2.49	5.97
Preconditions	10	Complacent	3.18	9.83	1.78	5.51
Unsafe Acts	1	Incorrectly assess situation	3.96	10.04	1.99	5.04
Preconditions	23	Issues with processing equipment	3.18	8.83	1.78	4.95
Unsafe Acts	5	Failure to follow prescribed procedure	3.96	8.04	1.99	4.04
Preconditions	15	Trained inadequately on process or tasks	3.18	6.83	1.78	3.83
Organizational	35	Failure in communicate/implement	4.73	7.27	2.18	3.34
Unsafe Acts	22	Failure to properly prepare for job/task	3.96	6.04	1.99	3.03
Preconditions	17	Failure to communicate/coordinate	3.18	4.83	1.78	2.71
Preconditions	39	Inadequate info or work instructions	3.18	4.83	1.78	2.71
Organizational	4	Training programs inadequate	4.73	5.27	2.18	2.42
Preconditions	6	Failure to be job qualified	3.18	3.83	1.78	2.15
Unsafe Acts	16	Use improper method	3.96	4.04	1.99	2.03
Organizational	9	Inadequate maintenance for process equipment	4.73	4.27	2.18	1.96

Controls

Since there was no limit to how many times a control could be identified in a review, unlike the error types, a statistical evaluation was not undertaken. Instead, partial lists of ranked frequencies are presented in Tables 5 and 6.

Table 5: Frequency of Identified Controls

Location 1 – Controls	Total
Missing Responsibilities and Lines of Authority	175
Missing Management System – Training	95
Missing Preventative Maintenance	92
Missing Mechanical Integrity	67
Management of Change	65
Pre-Startup Safety Review	45
Job Safety Analysis	21
Missing Contractor Training on Hazard Recognition	18
Missing Confined Space Entry	17
Lockout Tagout Procedure	14

Table 6: Frequency of Identified Controls

Location 2 - Controls	Total
Responsibilities & Lines of Authority	179
Missing Management System - Training	118
Job Safety Analysis - Final	72
Missing Preventative Maintenance Procedure	65
MOC Approval Form	29
Lockout Tagout - Final Rev	22
MOC Risk Screening Tool	21
Missing Specific MOC Work Instructions	16
MOC Level A-B PHA-What If	15
Process Hazards Analysis	15

Discussion

The results of the reviews paint a picture of an organization that needs more involvement and leadership from management. The most commonly cited control that failed to prevent the incident(s) was ‘Responsibilities and Lines of Authority’, a document that defines the responsibilities of upper management at each facility. This was commonly cited as a control because either those managers’ actions were not in accordance with the document or there were activities or processes for which no one was formally responsible. Problematic programs, including management of change, mechanical integrity, lockout tagout, and training, were also identified.

Lower on the list of controls were individual procedures that were identified as contributing factors. Often, simply knowing which controls to revise and understanding the human errors most often associated with those controls are sufficient for an organization to implement corrective action. However, organizations may benefit from further analysis, such as an HRA, on the identified procedures in certain instances. For example, if multiple human error types are associated with the control and the circumstances of the errors vary widely, further analysis might be appropriate.

Last year, Novich, Weidner, and Armstrong (2014) presented a case study of the HPR process at a chemical company. In that deployment, chemical company representatives conducted the HPR reviews after receiving training from the author’s company. This is in contrast with the current case study, where the author’s company alone performed the HPR reviews based on accident investigation data gathered by the subject company. The 2014 deployment was successful at finding preliminary patterns in human error occurrence. However, two difficulties were noted during that deployment: (1) it was challenging to coordinate the schedules of company representatives to conduct HPR reviews, and (2) the team's relative inexperience with the HPR process resulted, at times, in incomplete data, particularly regarding the controls associated with human error. The method of the current case study was designed to alleviate these difficulties by having a smaller team of HPR and PSM/Occupational Safety experts perform the reviews.

In the broader context of human error and occupational accidents and incidents, the methodology presented in this paper serves as a process to identify the human error types and the controls most frequently associated with an organization's incidents. From there, the organization can immediately identify local improvement efforts, evaluate aggregated data for systemic improvement opportunities, and/or determine the particular processes (if any) that may benefit from further analysis.

Limitations

While the HPR process appears to be an effective method for identifying human error types and controls in this case study, further replication would provide even stronger evidence of its utility. An additional limitation of this study is that the author's sole evaluation of the organization was incident data. Evaluating an organization's safety performance by only reviewing it at its worst could present a pessimistic and overly negative view of the organization's true safety performance or abilities. Additionally, the accident investigation results that were presented to the authors were not completed with the HPR review process in mind. As a result, there were instances where the information was insufficient to definitively state that a particular human error contributed to a certain incident.

Finally, while the authors have considerable expertise in applying the HPR process, they had limited knowledge of the characteristics of the refineries in question, including their culture, unwritten practices, employee engagement, and leadership effectiveness of supervisors and managers. This is in contrast to the aforementioned study (Novich, Weidner, & Armstrong, 2014), where the organization's review team had limited HPR experience but extensive knowledge and experience in company practices. The current case study appeared to generate more valid data, particularly regarding the controls associated with error, than the previous case study. Combining the strengths of these two methods may involve having HPR experts conduct a sampling of HPR reviews at the outset of a project, then turning the process over to organization personnel (after thorough training in the HPR process). Future empirical testing of this method will be needed to show whether it is superior to either of the case studies already presented.

Conclusion

The concept of human error and its contribution to occupational accidents and incidents has received considerable research attention in recent years. When an accident/incident occurs, investigation and analysis of the human error that led to the incident often reveals vulnerabilities in an organization's management system. There are many types of HRA, including THERP, HEART, and CREAM, that are designed to determine the relative probability that a human error will occur during a certain process. Unfortunately, many of these HRA methods are time-consuming to administer, require extensive expertise, and do not offer guidance on which processes to select for review.

This recent emphasis on human error has resulted in an expansion of knowledge related to human error and the most common factors contributing to incidents. HFACS, in particular, allows data from multiple incidents to be aggregated to discover patterns and trends in incident causation. HPR, a process developed by the author's company, adapts the framework provided by HFACS to further conceptualize and classify human error, but with the additional step of associating the control(s) that failed to prevent the incident from occurring. This process allows organizations to identify how and where to focus resources to drive safety performance improvements.

When the author applied HPR to two refineries at a petroleum refining company, the results uncovered an organization in need of more senior management involvement and leadership. Problematic programs, including management of change, mechanical integrity, lockout tagout, and training, were also identified.

The HPR methodology, while not without limitations, serves as a process to identify the human error types and the controls most frequently associated with an organization's incidents. This enables to organization to identify local improvement efforts, evaluate aggregated data for systemic improvement opportunities, and/or determine the particular processes that may benefit from further analysis. The evaluation of HPR as an effective analysis tool are ongoing, but early results suggest it may help companies understand human error within their organizations.

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