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Near misses in financial trading: skills for capturing and averting error

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PRECIS

We examine a cohort of near miss incidents collected from a financial trading organisation using the Financial Incident Analysis System (FINANS). We reveal that Situation Awareness and Teamwork skills appear universally important as a ‘last-line’ of defence for capturing error on the trading floor.

ABSTRACT

Objective: i) to determine whether near miss incidents in financial trading contain information on the operator skills and systems that detect and prevent near misses, and the patterns and trends revealed by these data and ii) to explore if particular operator skills and systems are found as important for avoiding particular types of error on the trading floor.

Background: In this study, we examine a cohort of near miss incidents collected from a financial trading organisation using the Financial Incident Analysis System (FINANS) and report on the non-technical skills and systems that are used to detect and prevent error in this domain.

Methods: 1,000 near miss incidents are analysed using distribution, mean, chi-square and associative analysis to describe the data, reliability is provided.

Results: Slip/lapse (52%) and Human Computer Interface (21%) often occur alone and are the main contributors to error causation, whereas the prevention of error is largely a result of teamwork (65%) and situation awareness (46%) skills. No matter the cause of error, Situation Awareness and Teamwork most often detect and prevent the error.

Conclusion: Situation Awareness and Teamwork skills appear universally important as a 'last-line' of defence for capturing error and data from incident monitoring systems can be analysed in a fashion more consistent with a safety II approach.

Application: This research provides data for ameliorating risk within financial trading organisations, with implications for future risk management programmes and regulation**.**

INTRODUCTION

Financial trading is an environment where staff are under pressure to take risks, and highly reliant on complex technical systems to complete their work. Human or system-related errors lead to ‘operational incidents’: where trading activity results in an avoidable loss (e.g. due to not assessing risk). Operational incidents place the integrity of the financial organisation at risk, and careful analysis of the underlying problems and recovery mechanisms are essential to maintaining organisational performance and long-term integrity. Through adopting principles used to manage risk in other-high risk domains (e.g. aviation, healthcare), research in financial trading has identified the factors underlying operational incidents: for example, teamwork skills, poor system interfaces, and slip/lapses (Leaver and Reader, 2016). These allow for an analysis of the underlying causes of operational incidents, and where appropriate remedies for stopping their occurrence on the trading floor (e.g. training, system redesign).

Yet, the reality of a complex and dynamic industry such as financial trading is that the nature of risk is likely to evolve, with the potential for human error remaining ever-present (Amalberti, 2013). To detect this evolution, the collection and analysis of near-miss data is essential (Barach & Small, 2000; Gnoni, & Lettera, 2012). This is where an error has occurred, but was detected and resolved before a loss was incurred. An error could be entering incorrect deal parameters (e.g. price, volume, maturity) into the system, a lack of communication between teams on a coordinated task (e.g. confirming and settling logistic information) or a bug in the system (e.g. sending timely breach reports). Analysing near misses can yield at least two important types of data. First, it can indicate emerging threats to organisational safety (e.g. in terms of systems, tasks, or skills deficiencies), and this is where much of the academic literature on incident reporting has focussed (Hopkins, 2001; NASA, 2001). Second, it can reveal the skills and behaviours that are important for navigating hazards and avoiding error after an incident has occurred, and in comparison, this latter aspect is less explored within the incident reporting research literature (Van der Schaaf, Lucas, & Hale, 2013).

Interestingly, this distinction reflects the debate around "safety-I" and "safety-II" approaches (Hollnagel, 2014). Safety-I refers to approaches to safety that focuses on error reduction, whereas safety-II refers to approaches that focus on the successful navigation of hazards to ensure organisational objectives are met. In industries, such as financial trading, where risk-taking is integral to success, both approaches appear essential to effective risk management. Yet, in terms of utilising near miss incident monitoring to achieve this, the safety-II approach has been less utilised (Huber et al., 2009; Kleiner et al., 2015).

In the current study, we examine a cohort of near miss incidents collected from a financial trading organisation. Drawing on this set of data, we address the following objectives:

1. To determine whether near miss reports in financial trading contain information on the non-technical skills that enable operators to detect and prevent errors from escalating into failure, and the patterns and trends revealed by these data.
2. To illustrate how the skills and systems that cause and detect/prevent error interrelate, with the purpose being to establish whether particular operator skills and systems are important for avoiding particular types of error on the trading floor

This article aims to make three contributions. First, it reveals the operator non-technical skills that are important for ensuring near misses do not escalate to failure, and thus contributes to approaches for improving risk management in financial industries. Second, it systematically explores how data from incident monitoring systems can be utilised to identify operator non-technical skills and behaviours important for navigating hazards and avoiding error. Third, it considers how data from incident monitoring systems can be analysed in a fashion more consistent with a safety II approach.

Financial trading environments

The financial trading environment is where products (e.g. bonds, equities, commodities) are bought and sold by financial traders in order to manage investment portfolios and generate profit for investment banks, energy companies and brokers. Trading requires an ability to anticipate market trends (i.e. for buying and selling) and negotiate large wholesale trades. Due to the sums of money and time-pressure involved in trading, it is a well-paid but stressful occupation. It is also inherently risky, with reward systems incentivizing risk-taking that results in profit. Whilst this should reward analytical decision-making processes, profit can also emerge from 'noise trading' (irrational and erratic trading activities that reflect somewhat random decision-making), which in turn can negatively influence 'rational' trading (and therefore penalize logical decision-making).

The trading floor itself is a large, noisy and socio-technological space wherein traders (and support teams) watch monitors and interact by phone, internal chat systems or in small groups. Each desk is grouped as a specialized desk (e.g. according to financial instruments or commodities being traded), and the successful interactions across these heterogeneous desks shapes performance (Beunza, 2004). The spatial configuration of the trading floor is standardized to provide the socio-spatial resources for promoting a situated awareness or sense making capabilities (Beunza, 2004; Hicks, 2004). Workstations are in close proximity so to allow traders to communicate with each other, and in terms of joint activity, traders typically cycle between working alone and in collaborative teams. For example, they monitor other desks' activity, share information, and interpret the 'noise' of the floor (Hicks, 2004; Willman et al., 2006).

Recent work has conceptualised financial trading as a high-risk industry, where systemic failures are a product of human error, risk-taking, poor system design, and safety culture (Leaver & Reader, 2016; 2017; 2015), and have serious consequences for the organisations involved (e.g. fines, institutional collapse) and society at large (collapse in banking systems). Yet, it is a highly complex industry to study, because institutional success is simultaneously contingent on risk-taking behaviours (e.g. to make money) and error reduction (to avoid mistakes).

Learning from near-misses

Traditionally, financial trading is a domain in which incident data has not been collected, analysed, or learnt from. In other high-risk industries, this is central to identifying risks to organisational safety, and prioritising and designing changes for avoiding further mishaps (Phimister et al., 2003). Near misses in particular are useful for learning due to their frequent occurrence, and information on how events were/can be avoided in future (Barach & Small, 2000; Reason, 2008).

In order to identify the general characteristics of successful systems that collect and interpret near miss data, and to identify areas in which the field might develop, we consider a number of key research studies reporting on incident monitoring systems. Although the review is non-exhaustive, Table 1 lists six of the more commonly reported on incident-monitoring systems.

Table 1: Features of Incident Reporting Systems in High-Risk Domains

Author	Name of incident monitoring system	Domain	Type of data collected	Positive skills	Negative skills
Runciman, Webb, Lee and Holland, 1993. (AIMS)	AIMS	Aviation	2000 critical incident reports	N/A	System failure constitutes the bulk of the contributory factors, and human failure identified in approx. 80% of the cases
Staender, Davies, Helmreich, Sexton and Kaufman, 1997 (CIRS)	CIRS	Anaesthesia	60 anonymous critical incident reports via internet	Concluded they are unable to assess the educational importance of the CI reports	Contributory factor of communication in the operating theatre
Beckmann, Baldwin, Hart and Runciman 1996. AIMS-ICU	AIMS-ICU	Intensive care	536 critical incident reports obtained from seven ICU’s	N/A	Multiple contributory factors; 33% systems-based, 66% human factor based.
Billings, Lauber, Funkhouser, Lyman, Huff (1976)	ASRS (aviation safety reporting system)	Aviation	Voluntary, non-punitive, anonymous critical incident reports. 1407 reports in the first quarter of operation.	N/A	Phases of flight where the incident occurred were detailed, systems issues, navigation, ground hazards etc.
Davies, Wright, Courtney and Reid, 2000.	CIRAS (Confidential Incident Reporting and Analysis System)	Rail	Gathers data in three ways; initial report form or telephone call, structured follow-up telephone questionnaire, in-depth interview with a researcher.	N/A	Fatigue, lapses of attention, breaches of procedure, problems with equipment
CHIRP Charitable	CHIRP (Confidential Human factors	Aviation	Confidential reports from pilots, flight	N/A	Does not formally request information on the

Trust, 1999	Incident Reporting Programme)	deck personnel, licensed engineers, maintenance workers in the airline industry.	contributing / mitigating factors, how the incident was discovered, or suggested corrective actions

As table 1 indicates, there is no established standard for the design and implementation of incident monitoring systems yet there are a number of common features (Gnoni et al., 2013; Goldenhar, Williams, & Swanson, 2003; Wu et al., 2010).

Most systems confidentially and anonymously collect data on consequential incidents and near misses. Analyses often focus on the causes of incidents (e.g. fatigue, communication), and these data are used to specify improvements in systems and skills (e.g. teamwork) for avoiding future recurrences (Barach & Small, 2000; Reason, 2008). Near misses (where due to luck or intervention, harm did not occur) are seen as particularly important to analyse due to them indicating the potentiality for consequential events (e.g. accidents). They can both indicate the causes of an incident, and also the processes and behaviours that prevent incidents becoming harmful (e.g. indicating the robustness of systems). For example, in reporting on the NASA Aviation Safety Reporting System, Sarter and Alexander (2000) have described how errors in aviation are often detected and ameliorated through routine checks (Sarter & Alexander, 2000). Data on error detection and recovery has been gleaned from near miss data in various domains (Abeysekera et al., 2005; Baysari et al., 2009; Lewis et al., 2009; Wu, Pronovost, & Morlock, 2002), with researchers examining the processes, countermeasures, and cues for detecting error and responding to error (Kessels-Habraken et al., 2010; Patel et al., 2011).

Nonetheless, and overall, the incident reporting literature has tended to focus on the causes of incidents, and the systems and skills required to minimise these (e.g. within the systems reported in table 1). Less work (and none in financial trading) has systematically examined the operator skills required for detecting and recovering from human error (i.e. near misses). For example, non-technical skills theory has been applied to systematically categorise and interpret the staff behaviours and activities leading to near misses (Reader et al., 2006), and to use these insights to suggest behaviours optimal for maintain safety. However, to our knowledge, this approach has not been taken to systematically analysing near misses. Yet, this might be useful in order to identify and train the key skills and behaviours that are found to underlie the detection and recovery of different errors and problem types. This is a somewhat positivistic perspective on incident reporting, and is consistent with Amalberti's (2013) description of 'ultra-resilient' organisations and Hollnagel's (2014) conceptualisation of "Safety-II" (Amalberti, 2013; Hollnagel, 2014).

Ultra-resilient organisations relate to the observation that in many dynamic and fast-moving industries that manage risk, it is not possible - or in some cases desirable - to entirely engineer risk out of the system. For example, this phenomena is observed in healthcare where procedures that create alternative risks for patients are necessary to the delivery of treatments (Reader, Reddy, & Brett, 2017), deep-sea fishing where workers operate in dangerous weather conditions (Amalberti, 2013), or financial trading where some risk-taking is necessary to achieve competitive advantage (Leaver & Reader, 2017). In these cases, risk is managed through improving employee skills and system design, and ensuring that where risk-taking is not successful, loss is avoided. Reflecting this, the "safety-II" approach argues that safety management involves a mixture of both error reduction ("safety-I") and also the identification of the skills and behaviours that enable things to go well (and in particular to navigate hazards). We explore this in the domain of financial trading.

CURRENT STUDY

In the current study, and using a previously established incident analysis tool, we examine whether near-miss reports in financial trading yield data that is useful and can be reliably coded in terms of the operator skills (and systems that support them) that prevent incidents from being realised (i.e. causing losses). For the first time, we place this phenomenon within a non-technical skills framework, and do so in order to augment previous research outlining the operator skills and behaviours that underlie effective risk management in financial trading.

Research Questions

Our research addresses the following two questions.

First, we determine the extent to which the near miss data collected on the trading floor contain reliably analysable information on human factors skills that contribute to, and prevent, errors. Through analysing these data, we identify the frequency and nature of operator skills and systems that ameliorate near misses. For example, how teamwork skills such as coordination (e.g. cross checking of information on shared tasks) and situation awareness skills such as attention (e.g. during routine task work) are key to capturing error on the trading floor. In terms of financial trading, relatively little is known about how error is averted on the trading floor. To explore this, we use a human factors framework designed specifically for providing insight into the skills used to detect and ameliorate error on the trading floor (the Financial Incident Analysis System: Leaver & Reader, 2016).

Second, we establish whether particular operator skills and systems are important for avoiding particular types of error on the trading floor (i.e. combinations). This will reveal whether there are specific skills required for managing particular errors, and yield implications for training and error management strategies in financial trading.

METHOD

FINANS

This study utilises data collected using the Financial Incident Analysis System (FINANS). FINANS is a confidential, voluntary incident reporting system designed with input from other incident reporting systems in similarly high-risk domains such as the Aviation Safety Reporting System (ASRS) in aviation. FINANS provides a standardised method for collecting data on operational incidents that occur on the trading floor, a reliable method for analysing and extracting human factors related contributors to operational incidents, and practical insight into how these contributors might be ameliorated. A fuller explanation of the merits, reliability and theoretical foundations of the FINANS tool can be found in Leaver and Reader (2016).

Fundamentally, the system comprises two parts. The first part is the ‘incident log’. To recap, an incident in this context is an event that did lead to (e.g. failure) or could have led to (e.g. near miss) losses or unwanted market or credit risk exposure. Incidents can be wide-ranging, and include technical systems error (e.g. pricing tool failures), erroneous human input errors, misunderstandings of instructions or procedures between departments (e.g. between a trader and their risk department), and rule violations (e.g. late trade entry). This first part of the system has several functional components that must be filled in by the reporter: identification of the team who detects the events, identification of the origin of the error (by team), date of event occurrence and detection and a free form verbal description of the event. Once the event is entered into the log, the incident is coded by the analyst (lead author). Data is aggregated and analysed in terms of descriptors for each incident (e.g. consequences, where and when incidents occurred). The log is accessible to all trading department staff on their local workstations and reports are regularly submitted by traders, risk control analysts (e.g. middle office and back office) as well as operators.

The second part of FINANS is a taxonomical system for interpreting incidents and near misses in terms of contributory factors. The taxonomy consists of a 'category' and 'element' (sub-category) levels. Categories function at a relatively generic level (e.g. situation awareness), and elements reflect aspects of activity specific to the trading floor environment that illustrate the categories (Flin & Patey, 2011). Moreover, each incident can potentially be coded within FINANS as single or multiple category and subcategory levels. For example, an incident may be identified as caused by teamwork (subcategory coordination) or teamwork (subcategory coordination) as well as situation awareness (sub categories attention and gathering of information). The full taxonomy used to codify the incidents is provided in Table 2 below.

Table 2. FINANS Human Factors Taxonomy

Category	Associated Elements
Situation Awareness	• Attention (distraction, lack of concentration, divided or overly focused attention) • Gathering information (poorly organised information, not enough gathering of information) • Interpretation of information (miscomprehension, assumptions based on previous experience) • Anticipation (i.e. thinking ahead, judging how a situation will develop) • Other

Teamwork	• Role and Responsibilities (e.g. unclear segregation of roles) • Communication and exchanging of information between team members • Shared understanding for goals and tasks • Coordination of shared activities • Solving conflicts (e.g. between team members and teams) • Knowledge sharing between teams • Other
Decision Making	• Defining the problem • Cue recognition (e.g. finding and recognising the cues to the decision) • Seeking advice on a decision • Noise and distraction (e.g. that reduce capacity to take a decision) • Bias and heuristics (e.g. over optimism, over confidence) • Other
Leadership	• Authority and assertiveness (e.g. taking command of a situation) • Listening • Prioritisation of goals (e.g. team / organisational) • Managing workloads and resources • Monitoring activity and performance of team members • Maintain standards and ensuring procedures are followed • Other
Slip/Lapse	• Fat Fingers • Procedural (not following a protocol, or following a protocol incorrectly) • Routinized task (e.g. a loss of concentration) • Forgetfulness (forgetting information, or how to perform an activity) • Memory • Distraction • Other
Human Computer Interface	• Use of the Tools (e.g. spread sheets) • Training on the tool • System did not detect the error • Design of the software and application • Maintenance and testing of the tool • Other

The second part of FINANS importantly allows us collect human factors data through the coding framework in order to extract information on the human factors skills that influence error on the trading floor and provides more fine grained insight into the skills (e.g. team communication and coordination) and behaviours (e.g. cross checking with team members) that are important for averting error.

Procedure

FINANS was used to collect incident reports in the participating organization from January 2014 until January 2016. With the support of the organisation, traders and trading support staff were briefed on human factors, non-technical skills and data entry in the system in advance of the deployment of the incident log and then asked to report the incidents in the log.

Following each reporting month, a trained human factors expert provides feedback reports (e.g. historical trends, evolving patterns of risk types) to the participating staff and management. Over this period, 1,042 unique incident reports (i.e. each incident reporting on a problematic trade was different) detailing an operational incident were collected and deemed suitable for analysis (e.g. clear text and a near miss event).

Near miss occurred in 96% of the selected errors (e.g. 1,000 cases of near miss, 42 cases of failure). Of the 1,000 near miss incidents, the lead author coded all the cases; 250 (25%) were coded by a human factors expert in order to provide a reliability assessment for coding.
For the purpose of this study, the author only considered near miss incidents that were reported as the aim of the analysis is to uncover how the incidents are caught or detected within the organisation.

The coding process was made up of five steps; (1) selection of the relevant human factors skills category (e.g. situation awareness, decision making, teamwork, leadership, human computer interface, or slip/lapse), (2) the selection of the relevant subcategory (i.e. element) of non-technical skills (e.g. if situation awareness is chosen as a main category, the element(s) can be selected from; distraction, gathering information, interpreting information, anticipation of future states), (3) identification of single team or multiple teams, (4) identification of an on-going state or isolated nature of the incident, (5) indication of whether the error is near miss or a failure. Each of the 1,000 incidents were coded in these five steps twice: once to identify the set of codes dedicated to the causes of error (e.g. identifying what went wrong) and a second time to identify the set of codes dedicated to the skills and systems that led to the detection and prevention of error (e.g. identifying what went right). The human factors codes used in FINANS have been reliably used to extract the skills that underpin error in previous studies across a range of incidents (near miss and failure) (Leaver & Reader, 2016). The concepts that underpin the coding framework were identified through a literature review of relevant concepts in the financial trading domain, a review of existing systems successful in place in other high-risk domains and feedback from subject matter experts (Leaver & Reader, 2016). In this analysis, we follow the assumption that the skills that underpin error are similar to the set of skills used to ameliorate error (Flin, O'Connor, & Crichton, 2008).

ANALYSIS

The results section reports on the following three analyses.

First we assess the reliability of coding for determining the causes of near misses, and the identification of factors that led to their detection and prevention. To do this, we present the reliability between the two expert coders using Cohen's kappa statistic in order to assure the coding outcomes are consistent and robust (Fleiss, Cohen, & Everitt, 1969; LeBreton & Senter, 2007).

Second, to identify the frequency with which various human factors skills cause and - for the first time in human factors literature - ameliorate near misses we undertake a frequency analysis of the coded incidents. This involved analysing the coded dataset to ascertain how often each code or group of codes occurs across the whole dataset in order to infer the most influential (e.g. highest occurrence) and least influential (e.g. lowest occurrence) skill categories. For example, this analysis reveals which skill problems are most likely to generate error (e.g. ‘fat fingers’) and which skills are most commonly drawn upon to capture error (e.g. attention).

Third we undertook an analysis of the skills and systems used to detect and prevent error and the causes of error together, the purpose of which is to illustrate how the skills that cause error and the skills that ameliorate error may interrelate. Specifically, by examining the frequency of occurrence (or otherwise) of every binary combination of skills we assess the relationships within the human factors codes separately for the causes of error and skills and systems that led to the detection and prevention error. For example, we explore whether, when near misses are remediated by teamwork skills, do situation awareness skills also tend to play a role in the remediation too, or do the two factors not occur together? This analysis helpfully contextualises the human factors findings and promotes a deeper understanding of how error is captured on the floor.

RESULTS

Financial trading staff reported 1,000 near miss incident reports through FINANS from January 2014 to January 2016. Near miss events accounted for 96% of reported errors within this time period (where 4% were classified as failures). This equates to less than 1% of trades within the company, and due to the data being generated through staff self-reporting, is likely to be an underestimation.

Reliability Analysis

We examined the reliability of coding between the author and a human factors expert. Of the 1,000 incidents, the lead author coded all the cases; 250 (25%) of the cases are coded by the third author to provide reliability assessment. Those cases were randomly selected from the batch. All incidents had at least one code from the FINANS taxonomy applied to explain the incident (e.g. incidents can be coded as multiple categories and elements). At the category level, the reliability was generally good or substantial[1] across both positive and negative categories.

For the causes of error at the category level, the reliability was good for situation awareness (k=0.499 and teamwork (k=0.567) and substantial for leadership (k=0.647), slip/lapse (k=0.65) and human-computer interaction (k=0.748).

	Cause of Error		Prevention of Error	
	Cohen's κ	p-value	Cohen's κ	p-value
SA	0.499	<0.001	0.549	0
TMWK	0.567	<0.001	0.503	<0.001
DM	-	-	-	-
LD	0.647	<0.001	0.453	<0.001
SL	0.65	<0.001	-	-
HCI	0.748	<0.001	0.655	0

	Cause of Error			Prevention of Error		
	Cohen's κ	Agreement	p-value	Cohen's κ	Agreement	p-value
SA	0.499	Good	<0.001	0.549	Good	0
TMWK	0.567	Good	<0.001	0.503	Good	<0.001
DM	-	-	-	-	-	-
LD	0.647	Substantial	<0.001	0.453	Good	<0.001
SL	0.65	Substantial	<0.001	-	-	-
HCI	0.748	Substantial	<0.001	0.655	Substantial	0

Figure 1: Kappa and p values for factors causing or ameliorating error

[1] Good reliability: 0.41 = k = 0.60 and substantial reliability 0.61 = k = 0.80 (McHugh, 2012)

Cohen's κ and p-values were not calculated where there were fewer than five instances of the factor causing or ameliorating error as these statistics would not be robust.

For the skills and system that led to the detection and prevention of error reliability was good for situation awareness (k=0.549), teamwork (k=0.503), leadership (k=0.453) and substantial for human-computer interface (k=0.655). For the detection of error coded in this study, slip/lapse was never chosen. This result is expected due to the nature of the slip/lapse categories (e.g. fat fingers, forgetfulness) that would not detect error, but primarily be the cause. Furthermore, as decision-making was never chosen in the coding, there are no reliability statistics for this category. This result is similar to previous studies where decision-making was rarely chosen when coding incidents (Leaver & Reader, 2016).

This shows that near miss incidents collected in the financial trading domain can be reliably coded for human factors and contain relevant information of the skills that cause error and for the first time, indicate that the critical incidents contain information of the skills / behaviours that are used to capture error on the trading floor.

Skills and systems for detecting error

Our first analysis establishes the extent to which near-miss data contains information on the skills and systems for detecting and preventing error. To provide an overview of the data, Table 3 details the occurrences of each human factor category and element used in FINANS to classify the causes of error and the skills that led to the detection of error.

Table 3: Frequency of human factors categories and elements found in the cases (n=1,000)

	Causes of error	Skills and systems that led to the detection and prevention of error

Category	Category Count (% overall)	Subcategory	Subcategory Count (% within category)	Category Count (% overall)	Subcategory	Subcategory Count (% within category)
Situational Awareness	130 (13%)	Anticipation	12 (9%)	460 (46%)	Anticipation	102 (22%)
		Attention	78 (60%)		Attention	123 (27%)
		Gathering Information	40 (30%)		Gathering Information	161 (35%)
		Interpreting Information	7 (5%)		Interpreting Information	48 (10%)
Teamwork	205 (21%)	Communication	53 (26%)	646 (65%)	Communication	96 (15%)
		Coordination	70 (34%)		Coordination	112 (17%)
		Roles and Responsibilities	79 (39%)		Roles and Responsibilities	340 (53%)
		Shared Understanding	39 (19%)		Shared Understanding	79 (12%)
Decision Making	11 (1%)	Bias and Heuristics	9 (82%)	14 (1%)	Bias and Heuristics	0 (0%)
		Cue Recognition	3 (27%)		Cue Recognition	14 (100%)
Leadership	113 (11%)	Maintaining Standards	27 (24%)	21 (2%)	Maintaining Standards	3 (14%)
		Monitoring Activity	87 (77%)		Monitoring Activity	17 (81%)
Slip/Lapse	523 (52%)	Fat Fingers	343 (66%)	2 (0.2%)	Fat Fingers	1 (50%)
		Memory	56 (11%)		Memory	0 (0.0%)
		Procedural	126 (24%)		Procedural	0 (0.0%)
Human-Computer Interaction	211 (21%)	Maintenance and Testing	123 (58%)	154 (15%)	Maintenance and Testing	1 (0.6%)
		System Detection	29 (14%)		System Detection	84 (55%)
		Use Of Tools	63 (30%)		Use Of Tools	50 (33%)

In terms of using FINANS to better understand the human factors that support the detection of error in the trading domain, Table 3 shows that all near miss were coded with a human factors category, with over half the near miss being caused by slip/lapse (52%) and ameliorated by teamwork (65%). The sections below provide a granular description of the skills that cause error and the skills that help trading staff capture error (e.g. near miss incident).

Causes of error. Table 3 confirms the findings of previous studies of causes of error using FINANS (Leaver & Reader, 2016). The majority of the errors are a product of slip/lapse (52%) problems and issues in human computer interaction (21%). The least coded category was decision making (1%).

In absolute terms, the most commonly coded element was fat fingers (343), followed by procedural (126) and maintenance and testing of systems (123). As seen in previous studies using FINANS, some elements were rarely coded; interpreting information (7), cue recognition (3), and bias and heuristics (9); however, unlike previous studies, each element was coded at least once in the data coding process.

Skills and systems that led to the detection and prevention of error. Table 3 indicates that overwhelmingly the error is detected and prevented by teamwork skills (65%) followed closely by situation awareness (46%). Human computer interface skills were identified in 15% of the near miss. The least coded category was slip/lapse (0.2%), followed by decision-making (1.4%) and leadership (2%).

In terms of elements, the most commonly coded was role and responsibilities (340), gathering information (161) and attention (123). Some elements were rarely coded for such as bias & heuristics (0), fat fingers (1), procedural (1), memory (0) and maintenance and testing (1).

Our analysis of the frequency of human factors in the set of collected near miss incidents shows that slip/lapse and human computer interface are the leading cause of error in the financial trading domain, and for the first time in human factors literature, identifies that teamwork and situation awareness skills are essential to capturing and preventing error.

To illustrate the context of the data collection (and the potential for intervention), and the types of problems and skills being identified using FINANS, Table 4 provides a sample of characteristic codified examples.

Table 4: Example data that could be reported and codified through FINANS

Incident Description	Human Factors problems identified in the cases	Specific behaviours that helped to ameliorate the error
Deals were downloaded with incorrect prices, and the wrong market parameters were sent into pre-publication. The error was picked up when a second team member noticed a discrepancy	Situation awareness (attention) Human computer interface (use of tools)	Teamwork (roles and responsibilities) Situation awareness (attention, gathering information)
A change in a contractual item not communicated between the relevant teams and noticed during a transaction booking	Teamwork (communication)	Situation awareness (gathering information, interpreting information) Teamwork (seeking out information through informal communication)
Entering an extra digit on the price (e.g. 0.01 versus 0.1)	Slip/lapse (fat fingers)	Teamwork (roles and responsibilities) Situation Awareness (attention)
Out-dated procedures not updated in the shared communication platform can lead to problems in task handover	Slip/lapse (procedures), situation awareness (anticipation)	Leadership (maintaining standards), teamwork (roles and responsibilities, coordination) Situation awareness (anticipation)
A hedge transacted by one team member for the group exposure with delayed communication about the details, meaning that hours are lost determining an alternate hedging scenario	Teamwork (coordination & communication) Slip/lapse (procedural)	Situation awareness (gathering of information) Teamwork (roles and responsibilities)
The price and volume of the deal were inverted	Slip/lapse (fat fingers, distraction)	Teamwork (roles and responsibilities) Situation awareness (attention)

Table 4 reveals some key features of the reported data: it typically generates from a principal cause and then travels through various social (e.g. teamwork) and/or cognitive (e.g. situation awareness) layers of defence. For example, error on the trading floor is characteristically caused by slip/lapse error (e.g. 'fat fingers'), this might then be compounded by a missed check at the risk control stage (e.g. missing a step in the role's stated goals and procedure) and subsequently detected through a secondary cross-check by another alert team member or the back office team before processing the trade (e.g. cross checking information of another team member)

To expand on the observation that error may be captured due to the interaction of multiple skill competencies, we undertook an analysis of the skills and systems used to detect and prevent error and the causes of error together, the purpose of which is to illustrate how the skills that cause error and the skills that ameliorate error may interrelate.

Associations between the causes of error and the skills and systems that detect error

In this analysis we assess whether there are particular relationships within the human factors codes for the causes of error and the skills that led to the detection of error. For example, the data collected through FINANS indicate that near misses are most often remediated by teamwork skills and situation awareness skills, but how often do these categories occur together or in isolation? Are these skills remediating a typical set of causes? This analysis is exploratory in design and aims to examine whether patterns emerge from the coding that shows how error emerges, migrates and is captured on the trading floor.

Associations between the causes of error. Of the 1,000 near miss incidents, 195 had more than one cause of error. Slip/lapse, the most common cause of error, nearly always occurred in isolation. This means that the causes of error are principally one skill or another (e.g. slip/lapse or human computer interface) and less often the result of multiple skill problems.

Associations amongst the skills and systems used to detect and prevent error. Multiple factors were more common for the skills and systems that detect and prevent error than the causes of error. Of the 1,000 near miss incidents, 295 had more than one skill or system that detected and prevented error. In over one third of cases where decision-making, slip/lapse, teamwork, or leadership were identified as factors, situational awareness was also identified as a preventative factor. Due to the low number of incidents were decision-making, slip/lapse, and leadership were identified as preventative factors, the relationship with situational awareness was only statistically significant for teamwork (χ_1^2 = 138.38, p<0.001). Nearly one-third of the 646 near miss cases where teamwork was a factor, situation awareness was also identified as a factor (208).

This means that the human factors responsible for causing (81%) and ameliorating (71%) near miss incidents therefore predominantly occurred in isolation. Exceptionally, teamwork and situation awareness, the two most frequent human factors responsible for ameliorating near misses, were the most likely to occur together doing so in just under half (45%) of all near miss where situation awareness prevented a near-miss. This analysis reveals that regardless of the cause of the error, situation awareness and teamwork are the leading skills used to capture and prevent error.

The association analysis preformed in this study shows that slip/lapse and human computer interface often occur alone (χ_1^2 = 249.79, p<0.001) and are the main contributors to error causation, whereas the prevention of error is largely a result of teamwork and situation awareness skills. Moreover, regardless of what causes the error, teamwork and situation awareness are the preventative skills that protect the organisation from error.

Situation awareness and teamwork skills appear universally important as a ‘last-line’ of defence for preventing trading mishaps, no matter the cause. The specific skills that are important to capturing error (e.g. gathering of information, attention) are supported through processes such as the ability to ask questions, alertness, participatory engagement and collaborative working groups. Teamwork skills such as roles and responsibilities, coordination and communication are also critical. These skills are supported by a strong perception of shared responsibility over team tasks and goals, cross-departmental team working sessions and communication aids such as internal messaging services, break out spaces and global virtual chat rooms.

DISCUSSION

This study identified the role of operator skills and systems for causing and preventing error in the domain of financial trading. It revealed the following.

First, similar to past studies (Leaver & Reader, 2016), slip/lapse related errors (e.g. fat fingers) are the most frequently coded skill category (52%). These most often occurred in isolation from other human factors problems. Issues around human computer interaction are the second most commonly coded human factors issue (21%), with human computer interfaces compromising the effective gathering and interpretation of information by users.

Secondly, and less examined within the literature, near-miss reports contain useful information about the operator non-technical skills that detect and prevent error. They report the attributes and behaviours that prevent errors from becoming realised losses. Whereas errors in financial trading are predominantly caused by slip/lapse and human-computer interface problems, most near miss are averted by good situation awareness (46%) and teamwork (65%) skills. The skills occurred in concert, with trading staff vigilance for arising issues (and understanding what they look like, and when they occur) and abilities to work with others to resolve them (e.g. sharing calculations and task critical information) being essential.

Third, and building on the previous point, no matter the causes of near misses, situation awareness and teamwork were the key skills for detecting and preventing them. This is to say, situation awareness and teamwork skills appear universally important as a ‘last-line’ of defence for preventing trading mishaps, no matter the cause. The specific skills that are important to capturing error (e.g. gathering of information, attention, roles & responsibilities) are supported through processes such as the ability to ask questions, alertness, participatory engagement and collaborative working groups. Teamwork skills such as communication between team members (e.g. following complex handover of tasks) and clear team roles and responsibilities (e.g. vigilance in verifying the data and conclusions published within the team's daily reports) are also critical.

Theoretical implications

The research findings demonstrate the value of analysing near misses in terms of the operator skills and systems that prevent the realisation of loss. Through FINANS, a non-technical skills perspective was adopted to interpret the 'safety nets' that prevent everyday errors and problems from resulting in error. This found the vigilance and cooperative behaviours of financial trading staff to be critical in identifying errors and problems that were produced by system-related issues (e.g. human computer interfaces) and slip/lapses. This supports previous observations within the incident reporting literature. For example, in terms of incident reporting data revealing the checks, routines, processes, and cues used by operators to identify and ameliorate error, meaning they become 'near misses' rather than consequential events (Abeysekera et al., 2005; Baysari et al., 2009; Patel et al., 2011; Sarter & Alexander, 2000). Associating error types and the skills that are used to detect them is novel and this information can be used to improve risk management in this domain.

The finding that error detection privileges the team working together resonates with the broader literature on non-technical skills and error detection and recovery. For example, in terms of recognising and recovering from error (Nikolic & Sarter, 2007) the social behaviours (e.g. communication) used to recover errors (de Leval et al., 2000), the importance of cross-checking behaviours (Kontogiannis & Malakis, 2009), and the consequences of operators not identifying errors (Kessels-Habraken et al., 2010). For situation awareness, the literature has previously shown attentional problems to underlie error and incidents, and to a lesser extent (and not in terms of incident reporting) the role of situation awareness in hazard detection (Underwood, Ngai, & Underwood, 2013). In terms of teamwork, our findings corresponds with research on the importance of cross-checking behaviours for avoiding error (Patterson et al., 2007), and communication and cooperative activities to avoid the escalation of errors into harm (Manser, 2009). The data collected in the current study points to the importance of team situation awareness processes in error detection and recovery (Endsley, 1995): for example in sharing and confirming understandings of the trading environment. This is relatively unexplored area within the situation awareness literature, and incident reporting more generally.

Thus, within domains such as financial trading, the insights that can be derived from near miss-data collected through incident reporting systems are both important for identifying the non-technical skill deficiencies that underlie error, and also the skills that support error detection and recovery (with teamwork and situation awareness being key). This is similar to other domains, and is especially important for financial trading, as the skills that are found to cause errors are difficult to eradicate and have limited margin for safety improvement (e.g. it is unrealistic to re-configure the system interface to perfection or eliminate all 'fat fingers' errors).

Synthesizing the skills that help capture error on the floor helps to build a more comprehensive understanding of the migration of error on the floor, leading to better-informed and wider reaching safety interventions. It accepts that risk is ever-present within the system, with human operators providing the last-line of defence. Incident reports have value in revealing what ‘goes well’ alongside ‘what goes wrong’ (Dekker, 2014). This links into “safety-II” approaches to human factors (Hollnagel, 2014), with near miss data collected through incident reporting systems representing a resource for identifying and recognising the value of everyday behaviours that support performance and the navigation of hazards. This is important in domains such as financial trading, where human factors approaches to managing risk require a delicate balance in terms of prescribing the conditions and systems requisite for ensuring a level of risk control, and also recognising the flexibility and skills of operators required for ensuring competitive advantage and the avoidance of losses.

Practical implications

In terms of organisational learning and risk management within financial trading, near misses provide useful insight.

First, the data indicates the importance of situation awareness and teamwork for capturing and resolving error. This has important implications for identifying the types of skills and behaviours that are valued by trading organisations, and might be shared and trained. Where incidents in financial trading do lead to losses, these can be significant. Well-trained (e.g. in terms of vigilance for types of problems, cooperative activities) operators may be able to reduce the conversion of near misses to ‘hits’. Although this is not a novel insight, for an industry such as financial trading, it is somewhat contrary to the socio-technological environment. In financial trading, performance is generally considered to be highly individualised (e.g. bonus allocation schemes rewarding top performers), with market knowledge and analytical skills being especially prized (Willman et al., 2002). Yet, our findings shed light on how the collective system acts as a protective layer for the organisation, with teamwork (e.g. roles & responsibilities) and situation awareness (e.g.

gathering of information and attention) skills being essential yet not currently recognised, recruited for, or trained. This perhaps also speakers to the role of organisational culture, and the importance of collaborative acts, responsibilities for risk management, and perceptions of management commitment to safety (Leaver & Reader, 2017).

Second, the data gives insight on organisational changes that might be deleterious for risk management. For example, the change or automation of technical systems that is important for operators to identify and spot errors (e.g. the automation of daily profit and loss calculations). Often in the trading domain, systems and interfaces are changed for business development needs, with insights from users and risk managers not being sought. Furthermore, trading is a highly globalised industry, with risk control functions increasingly being centralised to one geographical location (rather than being co-located with traders). The near-miss data revealed that cooperation between risk control teams and traders are often important for identifying and managing incidents, and changes to working structures may disrupt this. At the minimum, ensuring communication between these professional groups (e.g. using live running web cams or global chat rooms filtered by activity) would appear essential.

Importantly, the skills that have been identified as essential to capturing error (e.g. gathering of information, attention, roles & responsibilities) are supported through processes such as the ability to ask questions, alertness, participatory engagement and collaborative working groups and these are all behaviours that are promoted in a positive organisational (safety) culture. Although the error analysis undertaken in this study usefully guides us with granular insights into the behaviours that generate error and the skills that are used to capture error, these behaviours are positioned within a much larger cultural frame of the organisation. For example, the behaviours that drive the capture of error (e.g. taking the initiative to cross check team members work) are a product of the practises and norms that are encouraged and rewarded within the organisation. Understanding the culture is therefore important for explaining and changing negative and positive behaviours related to risk-management in financial trading.

LIMITATIONS AND FUTURE RESEARCH

The results are constrained by the nature of incident reporting generally, which is vulnerable to underreporting and incomplete information about incidents (O'Connor, O'Dea, & Melton, 2007). In the trading domain, the need for an individual to be aware that the event has occurred, their limited perspective on the incident, and their motivation to report constrain incident reporting. Furthermore, only one coder analysed all the near miss incidents (with a second coder analysing 25% of the near miss incidents to assess inter-rater reliability) and the data analysis was constrained by the clarity of the text and the potential biases of trading staff in recalling the incident. Moreover, the reliability analysis revealed scope for improving the FINANS taxonomy, and it may require further development to tailor it to near miss data. Issues such as stress, fatigue, and environmental factors (e.g. culture) were not examined and this could be the focus of future work. Moreover, the human factors research within this study refers to non-technical skills as 'skills' and in order to keep consistency refers to the additional set of human factors codes (e.g. slip/lapse, human computer interface) as 'skills' as well. Therefore the terminology around this may be somewhat confused (error within the non-technical skills literature is often observed as a problem in skill application).

CONCLUDING REMARKS

In the current study, we examined a cohort of near miss incidents collected from a financial trading organisation to identify the frequency and nature of operator skills and systems that ameliorate near misses and to establish whether particular operator skills and systems are important for avoiding particular types of error on the trading floor.

Our analysis reveals that the majority of the errors are a product of slip/lapse (52%) problems and issues in human computer interaction (21%). Our analysis of the reported near miss incidents show that overwhelmingly error is detected and prevented by teamwork skills (65%) followed closely by situation awareness (46%). Going further, our research reveals that slip/lapse, the most common cause of error, nearly always occurred in isolation. This means that the causes of error are principally one skill or another (e.g. skip/lapse or human computer interface) and less often the result of multiple skill problems. Exceptionally, teamwork and situation awareness, the two most frequent human factors responsible for ameliorating near misses, were the most likely to occur together doing so in just under half (45%) of all near miss where situation awareness prevented a near-miss. This analysis reveals that regardless of the cause of the error, situation awareness and teamwork are the leading skills used to capture and prevent error.

The outcomes of this research contribute to approaches for improving risk management in financial industries, and further exploring how near-miss data collected through incident monitoring systems can be analysed to determine the operator non-technical skills that underpin system safety.

DISCLAIMER

The study was undertaken by ML, AG and TR in their personal capacities. The opinions expressed in this article are the authors own and do not reflect the view of the participating organisation.

KEY POINTS

- Near miss incident analysis adds significant value to understanding how error is captured on the financial trading floor
- Human factors problems underlying error and the skills used to prevent error from escalating in the financial trading domain can be reliably identified and extracted by trained experts using the Financial Incident Analysis System (FINANS)
- Overwhelmingly, error is detected and prevented by teamwork skills (65%) and situation awareness (46%).
- Associative analysis reveals that teamwork and situation awareness are the most likely to occur together doing so in just under half (45%) of all near miss where situation awareness prevented a near miss. Meaning that regardless of the cause of the error, situation awareness and teamwork are the leading skills used to capture and prevent error.
- Our research provides novel evidence that data from incident monitoring systems can be analysed in a fashion more consistent with a safety II approach (i.e. identify good practice for mitigating, rather than reducing, error).

REFERENCES

Abeysekera, A., Bergman, I. J., Kluger, M. T., & Short, T. G. (2005). Drug error in anaesthetic practice: a review of 896 reports from the Australian Incident Monitoring Study database. *Anaesthesia*, *60*(3), 220–227.

Amalberti, R. (2013). *Navigating Safety: Necessary compromises and trade-offs. Theory and practice.* Heidelberg, Germany: Springer.

Barach, P., & Small, S. D. (2000). Reporting and preventing medical mishaps: lessons from non-medical near miss reporting systems. *BMJ: British Medical Journal*, *320*(7237), 759.

Baysari, M. T., Caponecchia, C., McIntosh, A. S., & Wilson, J. R. (2009). Classification of errors contributing to rail incidents and accidents: A comparison of two human error identification techniques. *Safety Science*, *47*(7), 948–957. Retrieved from http://yadda.icm.edu.pl/yadda/element/bwmeta1.element.elsevier-47633b21-ab91-310d-ab02-93fbea7bc00e

Beunza, D. (2004). Tools of the trade: the socio-technology of arbitrage in a Wall Street trading room. *Industrial and Corporate Change*, *13*(2), 369–400. http://doi.org/10.1093/icc/dth015

de Leval, M. R., Carthey, J., Wright, D. J., Farewell, V. T., & Reason, J. T. (2000). Human factors and cardiac surgery: a multicenter study. *The Journal of Thoracic and Cardiovascular Surgery*, *119*(4), 661–672.

Dekker, S. (2014). *Safety Differently: Human Factors for a New Era* (2nd ed.). Boca Raton: Taylor & Francis.

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *37*(1), 32–64.

Fleiss, J. L., Cohen, J., & Everitt, B. S. (1969). Large sample standard errors of kappa and weighted kappa. *Psychological Bulletin*, *72*(5), 323.

Flin, R. H., O’Connor, P., & Crichton, M. (2008). *Safety at the sharp end: Training non-technical skills*. (M. Flin, R. H., O’Connor, P., & Crichton, Ed.). Boca Raton: Ashgate Publishing.

Flin, R., & Patey, R. (2011). Non-technical skills for anaesthetists: Developing and applying ANTS. *Best Practice and Research: Clinical Anaesthesiology*. http://doi.org/10.1016/j.bpa.2011.02.005

Gnoni, M. G., & Lettera, G. (2012). Near-miss management systems: A methodological comparison. *Journal of Loss Prevention in the Process Industries*, *25*(3), 609–616.

Gnoni, M. G., Andriulo, S., Maggio, G., & Nardone, P. (2013). Lean occupational safety: An application for a Near-miss Management System design. *Safety Science*, *53*, 96–104.

Hicks, M. R. (2004). Trading system complexity. *Interactions*, *11*(4), 38–53. http://doi.org/10.1145/1005261.1005262

Hollnagel, E. (2014). *Safety-I and safety–II: the past and future of safety management.* Farnham: Ashgate Publishing, Ltd.

Hopkins, A. (2001). Was Three Mile Island a “Normal Accident”?. *Journal of Contingencies* *and Crisis Management*, *9*(2), 65–72.

Huber, S., van Wijgerden, I., de Witt, A., & Dekker, S. W. (2009). Learning from organizational incidents: Resilience engineering for high- risk process environments. *Process Safety Progress*, *28*(1), 90–95.

Kessels-Habraken, M., Van der Schaaf, T., De Jonge, J., & Rutte, C. (2010). Defining near misses: towards a sharpened definition based on empirical data about error handling processes. *Social Science & Medicine*, *70*(9), 1301–1308.

Kleiner, B. M., Hettinger, L. J., DeJoy, D. M., Huang, Y. H., & Love, P. E. (2015). Sociotechnical attributes of safe and unsafe work systems. *Ergonomics*, *58*(4), 635–649.

Kontogiannis, T., & Malakis, S. (2009). A proactive approach to human error detection and identification in aviation and air traffic control. *Safety Science*, *47*(5), 693–706.

Leaver, M. P., & Reader, T. W. (2017). Safety culture in financial trading: an analysis of trading misconduct investigations. *Journal of Business Ethics*. http://doi.org/10.1007/s10551-017-3463-0

Leaver, M. P., & Reader, T. W. (2017). Safety Culture in Financial Trading: An Analysis of Trading Misconduct Investigations. *Journal of Business Ethics*. http://doi.org/10.1007/s10551-017-3463-0

Leaver, M., & Reader, T. W. (2015). Non-technical skills for managing risk and performance in financial trading. *Journal of Risk Research*, *19*(6), 687–721. http://doi.org/10.1080/13669877.2014.1003319

Leaver, M., & Reader, T. W. (2016). Human Factors in Financial Trading: An Analysis of Trading Incidents. *Human Factors*, *58*(6). http://doi.org/10.1177/0018720816644872

Leaver M., & Reader, T. (2016). Human Factors in Financial trading. *Human Factors in Financial Trading: An Analysis of Trading Incidents*, *58*(6), 814–832. http://doi.org/10.1177/0018720816644872

LeBreton, J. M., & Senter, J. L. (2007). Answers to 20 Questions About Interrater Reliability and Interrater Agreement. *Organizational Research Methods*, *11*(4), 815–852. http://doi.org/10.1177/1094428106296642

Lewis, P. J., Dornan, T., Taylor, D., Tully, M. P., Wass, V., & Ashcroft, D. M. (2009). Prevalence, incidence and nature of prescribing errors in hospital inpatients. *Drug Safety*, *32*(5), 379–389.

M. Goldenhar, L., Williams, L. J., & G. Swanson, N. (2003). Modelling relationships between job stressors and injury and near-miss outcomes for construction labourers. *Work & Stress*, *17*(3), 218–240.

Manser, T. (2009). Teamwork and patient safety in dynamic domains of healthcare: a review of the literature. *Acta Anaesthesiologica Scandinavica*, *53*(2), 143–151.

McHugh, M. L. (2012). Interrater reliability: the kappa statistic. *Biochemia Medica*, *22*(3), 276–282.

NASA. (2011). *Accident precursor analysis handbook*. Washington.

Nikolic, M. I., & Sarter, N. B. (2007). Flight deck disturbance management: a simulator study of diagnosis and recovery from breakdowns in pilot-automation coordination.

Human Factors, *49*(4), 553–563.

O'Connor, P., O'Dea, A., & Melton, J. (2007). A Methodology for Identifying Human Error in U.S. Navy Diving Accidents. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *49*(2), 214–226. http://doi.org/10.1518/001872007X312450

Patel, V. L., Cohen, T., Murarka, T., Olsen, J., Kagita, S., Myneni, S., ... & Ghaemmaghami, V. (2011). Recovery at the edge of error: debunking the myth of the infallible expert. *Journal of Biomedical Informatics*, *44*(3), 413–424.

Patterson, E. S., Woods, D. D., Cook, R. I., & Render, M. L. (2007). Collaborative cross-checking to enhance resilience. *Cognition, Technology & Work*, *9*(3), 155–162.

Phimister, J. R., Oktem, U., Kleindorfer, P. R., & Kunreuther, H. (2003). Near- miss incident management in the chemical process industry. *Risk Analysis*, *23*(3), 445–459.

Reader, T. W., Reddy, G., & Brett, S. J. (2017).). Impossible decision? An investigation of risk trade-offs in the intensive care unit. *Ergonomics*, *In Press*.

Reader, T., Flin, R., Lauche, K., & Cuthbertson, B. H. (2006). Non-technical skills in the intensive care unit. *British Journal of Anaesthesia*, *96*(5), 551–9. http://doi.org/10.1093/bja/ael067

Reason, J. T. (2008). *The human contribution: unsafe acts, accidents and heroic recoveries.* Ashgate Publishing, Ltd.

Sarter, N. B., & Alexander, H. M. (2000). Error Types and Related Error Detection Mechanisms in the Aviation Domain: An Analysis of Aviation Safety Reporting System Incident Reports. *The International Journal of Aviation Psychology*, *10*(2), 189–206. http://doi.org/10.1207/S15327108IJAP1002_5

Underwood, G., Ngai, A., & Underwood, J. (2013). Driving experience and situation awareness in hazard detection. *Safety Science*, *56*, 29–35.

Van der Schaaf, T. W., Lucas, D. A., & Hale, A. R. (2013). *Near miss reporting as a safety tool*. Butterworth-Heinemann.

Willman, P., Fenton-O'Creevy, M., Nicholson, N., & Soane, E. (2006). Noise Trading and the Management of Operational Risk; Firms, Traders and Irrationality in Financial Markets. *Journal of Management Studies*, *43*(6), 1357–1374. http://doi.org/10.1111/j.1467-6486.2006.00648.x

Willman, P., Fenton-O'Creevy, M., Soane, E., & Nicholson, N. (2002, June 1). Traders, managers and loss aversion in investment banking: a field study. *Accounting, Organizations and Society*. Retrieved from http://oro.open.ac.uk/1307/

Wu, W., Yang, H., Chew, D. A., Yang, S. H., Gibb, A. G., & Li, Q. (2010). Towards an autonomous real-time tracking system of near-miss accidents on construction sites. *Automation in Construction*, *19*(2), 134–141.

Wu, A. W., Pronovost, P., & Morlock, L. (2002). ICU incident reporting systems. *Journal of Critical Care*, *17*(2), 86–94. Retrieved from http://yadda.icm.edu.pl/yadda/element/bwmeta1.element.elsevier-e4c86ffa-2061-3b71-b00e-581e7e248274