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USING NEURAL NETWORKS TO PREDICT HFACS UNSAFE ACTS FROM THE PRE-CONDITIONS OF UNSAFE ACTS

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ABSTRACT

HFACS (Human Factors Analysis and Classification System) is based upon Reason's (1990; 1997) organizational model of human error which suggests that there is a 'one to many' mapping of condition tokens (HFACS level 2 psychological precursors) to unsafe act tokens (HFACS level 1 error and violations). Using accident data derived from 523 military aircraft accidents, the relationship between HFACS level 2 pre-conditions and level 1 unsafe acts was modelled using an artificial Neural Network (NN). This allowed an empirical model to be developed congruent with the underlying theory of HFACS. The NN solution produced an average overall classification rate of *circa* 74% for all unsafe acts from information derived from their level 2 pre-conditions. However, the correct classification rate was superior for decision and skill-based errors, than for perceptual errors and violations.

PRACTITIONER SUMMARY

A model to predict unsafe acts (HFACS level 1) from their preconditions (HFACS level 2) was developed from the analysis of 523 military aircraft accidents using an artificial Neural Network. The results could correctly predict approximately 74% of errors.

KEYWORDS

HFACS (Human Factors Analysis and Classification System), Human Error, Neural Networks, Modelling, Accident Analysis

INTRODUCTION

Human Factors Analysis and Classification System and Human Error

The Human Factors Analysis and Classification System (HFACS) is currently the most widely used human error-coding framework for accident and incident analysis. HFACS is based on Reason's (1990) Generic Error Modelling System (GEMS) and subsequent 'Swiss Cheese' model, which places unsafe acts resulting in accidents within an organizational context (Reason, 1997). This model extends back into the organization to define the organizational and psychological precursors underlying an individual's inadequate performance. Many safety management models (including that promoted by the International Civil Aviation Organization, 2009) are based around the principles derived from Reason's work.

The development of the HFACS is described in a series of papers and books (e.g. Wiegmann & Shappell, 1997, 2001a, 2001b, 2001c, 2003; Shappell & Wiegmann, 2001, 2003, 2004). The HFACS model assumes active failures (those proximal to the accident) and latent failures (distal errors and misspecifications which lie dormant within the system) combine with other factors to breach a system's defences. As Reason (1997) noted, as complex organizations are managed by fallible human beings, it is not surprising that decisions and actions at an organizational level are implicated in accidents. Active failures of operators have a direct impact on safety but latent failures are often spawned in the upper levels of the management and related regulatory structures.

HFACS was originally designed as a framework for analysing human error in US naval aviation accidents (Wiegmann & Shappell, 1997; Shappell & Wiegmann, 2000) however it has also demonstrated its applicability to the analysis of large scale data sets of incidents and accidents, such as the analysis of accidents in US commercial aviation (Wiegmann & Shappell, 2001a, 2001b; Shappell, et al., 2007); US general aviation (Shappell & Wiegmann 2003, 2004); Australian general aviation (Lenné, Ashby & Fitzharris, 2008); African aviation (Munene, 2016); Bangladeshi civil aviation (Rajiba & Fan, 2015); Taiwanese military aviation (Li & Harris, 2005; Li & Harris, 2006a; Li & Harris, 2013); Taiwanese civil aviation (Li, Harris & Yu, 2008); Indian military aviation (Gaur, 2005); Australasian military operators (Hooper and O'Hare, 2013); offshore helicopter operations (Omole & Walker, 2015); and uninhabited air vehicles (Tvaranyas, Thompson & Constable, 2006).

Wiegmann & Shappell (2001b) claim that the HFACS framework bridges the gap between theory and practice by providing safety professionals with a theoretically based tool for identifying and classifying human errors in aviation mishaps. The framework focuses on both latent and active failures and their inter-relationships, and by doing so it facilitates the identification of the underlying causes of human error. It has shown high levels of inter- and intra-rater reliability when coding accident data (Li & Harris, 2006a; Cohen, Wiegmann & Shappell, 2015; Ergai, Cohen, Sharp, Wiegmann, Gramopadhye & Shappell, 2016) especially if the analysts are trained in its use.

HFACS analyses error at four levels, with each higher level presumed to affect the next downward level in the system. Level 1 'Unsafe acts of operators' is concerned with the active failures proximal to the accident (the 'sharp end') further sub-divided into two basic categories of errors and violations. Level 2 'Preconditions for unsafe acts' is concerned with the latent failures within a causal sequence of events, the context of substandard conditions of operators and the substandard practices they adopt. Level 3 'Unsafe supervision' concerns further latent failures in middle management which underpin the causal chain of events producing unsafe acts at the front-line. Finally, the highest organizational level, 'Organizational influences' (latent failures and system misspecifications, distal to the accident) encompasses the elusive latent failures associated with the fallible decisions at upper levels of management.

As noted earlier, HFACS is based upon Reason's model of error within an organizational context. In Reason's terminology, the actual error(s) themselves are designated as unsafe act tokens. There is a 'one to many' mapping of condition tokens (the things that increase the probability of an error being made) to unsafe act tokens. This is evident in the structure of HFACS when the relationship between the errors themselves at level 1, and the precursors to error (at levels 2-4) is considered. For example, HFACS level 2 is analogous to Reason's condition tokens. Any one (or more) condition token(s) may contribute to any one of hundreds of errors of omission or commission occurring in the cockpit (unsafe act tokens). Because of the nature of this relationship, Reason argued that it is almost impossible to work backwards from unsafe act tokens (HFACS level 1) to pre-condition tokens (HFACS level 2).

The above argument may be extended even further back in the accident causal sequence to Reason designates as function types. It is at this stage where organizational factors (the types) are translated into the individual's experience (the tokens). There are fewer function types than there are condition tokens, but again, it is almost impossible to back track from a condition token to a function type as a result of the one-to-many correspondence between types and tokens. These are captured in HFACS levels 3 and 4.

The 'one to many' (or even a 'many to one') mapping of condition tokens to errors, and of function types to tokens means that while Reason's model has explanatory power, its ability to predict unsafe acts is limited. A number of authors have examined the univariate relationship of HFACS lower level events to higher level factors (e.g. Li & Harris, 2006b; Tvaranyas, Thompson & Constable, 2006; Hooper and O'Hare, 2013; Daramola, 2014) which has suggested the existence of key relationships between errors at the operational level and organizational inadequacies at both the immediately adjacent level (preconditions for unsafe acts) and higher levels in the organization (unsafe supervision and organizational influences). This lends support to Reason's model which suggests that active failures on the flight deck are promoted by latent conditions higher in the organization. However, such analyses do not reflect the complex mapping of types and condition tokens to errors posited by Reason and which is also reflected in the HFACS framework. NN analytical techniques allow for the relationship of many factors at higher HFACS levels to be considered simultaneously with all categories of unsafe act. NNs go beyond simple linear causality (they include elements that both inhibit and excite nodes) and extend across all factors modelled in the system.

Neural Networks

Conventional statistical analytical techniques, either univariate or multivariate, cannot provide a tool to model the complex mapping of pre-cursors to errors (types to tokens) in Reason's model of organizational error. These statistical techniques can only cope with additive and/or multiplicative relationships between predictor and criterion variables. It is also difficult to predict more than a single criterion variable. Neural Networks (NNs) can cope with such complexities. However, previous authors that have used HFACS data as an input into a NNs (Liu, *et al*., 2013) have not reflected the underlying theoretical structure of errors and precursors in their analytical approach. In this case HFACS data were simply used as an input into the prediction of accident category (fatal/non-fatal) rather than a validation of the underlying theoretical structure or Reason's error model.

NNs have emerged in recent years as a data mining technique for exploring complex relationships in large datasets within the social sciences (Hair, *et al*., 1998; Garson, 1998). NNs allow the simultaneous prediction of many outcomes from many inputs, hence are ideal for predicting multiple HFACS outcomes at level 1 from pre-cursors at level 2. They are particularly well suited to applications with noisy, missing, overlapping, non-linear and non-continuous data (Moore, 1988) and can also handle highly unstructured data. This is typical of data derived from accident and incident reports. NNs provide a way of building an empirically describable and verifiable model of the relationship between inputs and outputs and allow for contextual information to be incorporated into a model (Haykin, 1994).

NNs have been used to model such diverse applications as stock market outcomes (Guresen, Kayakutlu & Daim, 2011); cancer survival (Burke *et al*, 1997);

marine accidents (Hashemi, Le Bland, Rucks & Shearry, 1995); predicting landing speeds (Diallo 2012); aircraft maintenance risk (Luxhøj & Williams, 1996) and naturalistic pilot decision-making (Duggan & Harris, 2001). The model-building approach in NN analysis also reflects the trend in Human Factors away from statistical tests of difference and toward developing process-engineering models of human behaviour (Moray, 1998).

NNs are based upon a simplified model of the hypothesised manner in which the brain operates but are by no means a replica of cognitive neural processes (Beale & Jackson, 1990). The most common form of artificial NN is the multi-layer perceptron (see figure 1). The basic NN processing unit is the node (neuron). A NN contains many nodes, representing input values and output values (derived from the dataset) plus one or two middle ('hidden') layers. It is the incorporation of the hidden layer(s) that allows complex relationships to be modelled. Each node is a self-contained unit that acts in parallel with other nodes. Every connection (synapse) between nodes has a weight (derived during the modelling process) that is applied to the incoming data. Each node then creates a summated value of these products, to which is applied an activation function (also derived during modelling) resulting in an output value from the node being determined. The activation function dictates the output of a node, which simply is either 'fire' (produce an output) or 'inhibit' (no output).

INSERT FIGURE 1 ABOUT HERE

The essential feature of NNs is that they learn the relationship(s) between inputs and outputs in the building process, and self-correct. They are trained by exposure to historical data in a supervised leaning set, with known inputs and outputs. In the supervised learning set, the model commences with a 'best guess' and applies a set of weights. The predicted outputs produced are compared with the actual, known outputs, and the weights in the model are revised iteratively through a back-propagation process (depending upon the sign and magnitude of the error observed) until the solution converges and the overall error rate falls below some pre-defined criterion. The predictive accuracy of NNs are typically reported to be between 70-100% (Duggan & Harris, 2001; Diallo, 2012; Liu, *et al*., 2013).

To validate the NN, the model is then applied to the input data from a cross-validation (unseen) data set and the output predictions from the network are compared to the known actual outputs.

Aims and Objectives

Scientific models must be empirically testable, hence they need to be embedded within a theory. They should offer predictions about outcomes (errors) on the basis of context and information (pre-cursors). A testable model can also be replicated and the bounds of its generalisability established. Reason's model of error proposes a 'one to many' mapping of condition tokens (the things that increase the probability of an error being made) to unsafe act tokens. In the HFACS framework this becomes a 'many to many' mapping of psychological precursors to errors. The objective of this study was to investigate if an NN using HFACS level 2 data

‘Preconditions for unsafe acts’ (condition tokens in Reason’s terminology) which includes including psychological, physiological, physical, environmental and technical factors, could be used as inputs to predict HFACS level 1 outputs ‘Unsafe acts of operators’ (unsafe acts tokens). Analysis was restricted to just these two levels as a result of limitations in the manner that NNs operate (with just one input layer and one output layer). However, HFACS analyses restricted to just levels 1 and 2 are not uncommon (e.g. Shappell & Wiegmann 2003, 2004; Lenné, Ashby & Fitzharris, 2008).

METHOD

Data

The source data were comprised of the narrative descriptions of accidents occurring in the Republic of China (RoC) Air Force between 1978 and 2002. The complete data set comprised all 523 aircraft accidents during this 25-year period comprising class-1 accidents (cost to repair over 65% of original purchase price and/or death of at least one crew member); class-2 accidents (cost to repair between 35 and 65% of purchase price and/or one or more crew member sustained serious injury); and class-3 accidents (cost to repair between 3-35% of original price and/or a crew member sustained minor injuries).

Classification framework

This study used the original version of the HFACS framework described in Wiegmann & Shappell (2003).

Level 1 of HFACS (‘unsafe acts of operators’) categorized events proximal to an accident in the four sub-categories of ‘decision errors’; ‘skill-based errors’; ‘perceptual errors’ and ‘violations’ (see figure 2). Level 2 of the framework (‘preconditions for unsafe acts’) has seven further sub-categories: ‘adverse mental states’; ‘adverse physiological states’; ‘physical/mental limitations’; ‘crew resource management’; ‘personal readiness’; ‘physical environment’, and ‘technological environment’. Level 3 of HFACS (‘unsafe supervision’) comprises of the sub-categories ‘inadequate supervision’; ‘planned inappropriate operation’; ‘failure to correct known problem’ and ‘supervisory violation’. Finally, the fourth and highest level of HFACS ‘organizational influences’ is formed from the four sub-categories of ‘resource management’; ‘organizational climate’ and ‘organizational process’. However, neither HFACS level-3 nor level-4 was used in the current study.

INSERT FIGURE 2 ABOUT HERE

Coding

Each accident report was coded independently by a Certified Aviation Psychologist (EAAP - European Association for Aviation Psychology) and an Instructor Pilot. Both coders were responsible for Human Factors training in the RoC Air Force and had also applied HFACS framework to analyse accident investigation reports to develop accident prevention strategies for ROC Air Force Headquarters. They were trained together on the HFACS framework for approximately 10 hours to ensure they achieved a detailed and accurate understanding of each of the categories and sub-categories. Following this, each accident report was then analysed independently. The presence (coded 1) or absence (coded 0) of an HFACS sub-category was assessed in each report narrative.

To avoid over-representation from any single report, each sub-category was counted a maximum of once per accident. Thus, the count simply signifies the presence or absence of a particular sub-category within a given accident.

DATA AND ANALYSIS

Data

Fighter aircraft were involved in 353 of the accidents in the data set; training aircraft in 113 accidents and cargo aircraft in 57 accidents. There were 206 class-1 accidents; 78 class-2 accidents and 239 class-3 accidents. In the accidents coded there was a grand total of 1,762 instances of sub-categories being used within the HFACS framework (see Li & Harris, 2005 and Li & Harris, 2006a). A complete description of the data set, broken down by HFACS sub-category is provided in table 1. Data in HFACS levels 3 and 4 have been omitted as it was not utilised in the following NN models (these data can be found in Li and Harris, 2006a). Inter-rater reliabilities calculated as a simple percentage showed reliability figures on a sub-category basis of between 72.3% and 92.2% indicating acceptable agreement between the two raters (the category 'Adverse physiological states' actually showed 96.4% agreement but was dropped from the analysis – see later).

INSERT TABLE 1 ABOUT HERE

Analysis

HFACS Level 1 variables (Unsafe Acts of Operators - Unsafe Act Tokens) were set as the dependent variable (output layer), with HFACS Level 2 variables (Preconditions for Unsafe Acts - Condition Tokens) as the predictor variables (input layer). As noted in the caption to table 1, the sub-category of 'Adverse Physiological States' was dropped as a result of having a very low frequency of occurrence in the data set. Having coded all the incident data as described earlier, the data set was randomly split into two portions. The larger set of 355 cases (69.7%) was used as the training set for the neural network; the smaller set of 154 cases (30.3%) was used as the data set to cross validate the solution derived (see Garson, 1998). Fourteen cases were excluded from the analysis as a result of missing data.

The data set was entered into the binary version of the NN analysis programme (IBM SPSS Version 24). As variables in both the input layer and the output layer were binary in nature, dummy variables were derived indicating the 'presence' or 'absence' of each HFACS category resulting in 12 variables in the input layer and eight in the output layer. Nine nodes were used in the 'hidden layer' based on the formula for the estimation of the optimum number of hidden nodes (Neuroshell, 1990) which is double the square root of the number of input nodes plus the number of output nodes. This number is also well within the maximum number of hidden nodes suggested by Garson (1998), which is half the number of cases in the training data set.

INSERT TABLE 2 ABOUT HERE

The figures in table 2 correspond to the weights on the paths from the input nodes to the hidden nodes (as described in figure 1). As the input nodes were of a binary format, coded '1' or '0', the weight also represents that path's contribution to making a hidden node fire (or not). A large positive weight will encourage a hidden node to fire: a large negative weight will help inhibit the node. The biases (calculated by the NN program) represents the threshold above which hidden node will fire. The hidden nodes also produce a binary output. The lower part of table 2 shows the connection weights between the hidden nodes and the output nodes (the decisions and actions taken). As the output from the hidden nodes is also binary, the weights are again essentially the contribution to making an output node 'fire'.

Overall, on the basis of the NN derived, 74.2% of all cases were correctly classified in the training sample and 73.4% in the cross-validation data set. The overall model summaries for the training and cross validation samples are presented in table 3. The accuracy of the NN derived to predict each of the HFACS level 1 errors ('unsafe actors of operators') from their pre-cursors at HFACS level 2 ('pre-conditions of unsafe acts') is presented in table 4.

INSERT TABLES 3 and 4 ABOUT HERE

The relative importance of the HFACS level 2 variables for predicting the error categories at level 1 is presented in table 5.

INSERT TABLE 5 ABOUT HERE

The results can be interpreted within a signal detection paradigm, where a 'hit' is the correct prediction of an error in an HFACS category from the level 2 precursors; a 'miss' is a failure to predict an error where one is actually observed within the accident report narrative; a 'false alarm' is incorrectly predicting the occurrence of an error, and a 'correct rejection' is predicting no error where none actually occurs.

Using this approach, the sensitivity index (SI) can be derived from the formula described by Stanton & Stevenage (1998):

INSERT EQUATION 1 ABOUT HERE

The closer the value calculated for the SI is to 1, the more accurate are the predictions made. SI values were calculated for the results from the cross-validation data set (see table 6).

INSERT TABLE 6 ABOUT HERE

To further evaluate the efficacy of the neural network solutions, A Kolmogorov-Smirnov 'goodness of fit' test was applied to the outputs from both the training and the cross-validation samples, comparing the distributions of the observed and predicted results (see Su & Chou 2006; Modarres, 2009; Liu, *et al*, 2013). In both cases the results were non-significant (training, $D=0.16$, $p>0.05$; cross-validation, D=0.12, p>0.05) suggesting the observed and predicted distributions were not significantly different. Following the approach described by Modarres (2009) Wilcoxon rank sum tests were also undertaken to establish if the neural network performed significantly better in one outcome group compared to the other (i.e. 'hits' versus 'correct rejections' – see table 2). Again, no significant difference between groups was observed in either case (training, Z=-1.46, p>0.05; cross-validation, Z=-1.82, p>0.05) suggesting the neural network did not perform better with respect to either outcome.

DISCUSSION

The NN solution derived to predict the HFACS level 1 categories of 'decision errors'; 'skill-based errors'; 'perceptual errors' and 'violations' from their level 2 pre-cursors of 'adverse mental states'; 'physical/mental limitations'; 'crew resource management'; 'personal readiness'; 'physical environment', and 'technological environment' was capable of producing an average overall classification rate of 74.2% in the training sample and 73.4% in the cross-validation data set. This overall result is toward the lower end of the typical range for the predictive accuracy of NNs of between 70-100% (Duggan & Harris, 2001; Diallo, 2012; Liu, *et al*, 2013).

Nevertheless, the results suggest that NNs are a viable option for mapping the 'one to many' (or 'many to many') relationship between 'pre-conditions of unsafe acts' (if using HFACS terminology) or 'condition tokens (if using Reason's 1990; 1997 terminology) and the 'unsafe acts of operators' (or 'unsafe act tokens'). This approach overcomes the limitations of statistical approached based upon the general linear model which only allow the prediction of a single criterion variable at a time (Li & Harris, 2006a; Tvaranyas, Thompson & Constable, 2006). Cross validation of the NN model derived using an independent data set allows the sample specificity of such a model to be verified. If the performance of the NN model on the cross-validation data set is comparable to the training data set from which it is derived, then there can be confidence that the solution derived will be generalisable. The performance of the NN model derived in this case is very similar in the case of both the training and the cross-validation data samples (see tables 3 and 4).

The data in table 5 suggest that the strongest predictors of unsafe acts at level 1 were 'physical/mental limitations' (a basic lack of physical/mental capability which adversely affects performance e.g. visual limitations or insufficient reaction time); 'crew resource management' (poor communication, coordination, leadership, planning and/or teamwork on the flight deck); and 'adverse mental states' (stress, workload, mental fatigue, situation awareness, motivation, etc.). This supports earlier work where on a uni-variate basis, these HFACS level 2 categories had been observed to be significant predictors of 'decision errors' and 'skill-based errors' (Li & Harris, 2006a).

As would be expected, the overall performance of the NN derived from the training sample was marginally superior to that in the cross-validation sample (average percent correct predictions 74.2% versus 73.4%, respectively – see table 3). However, the difference was so small as to suggest that the NN derived in the training sample was not over-fitting the data (i.e. capitalising upon chance inter-relationships between predictor and criterion variables) and that the NN model derived was generalisable (Hair, *et al.*, 1998). The model derived did, however, perform better when predicting some HFACS level 1 categories, compared to others. With regard to 'skill-based errors' and 'decision errors', the NN performed equally as well in predicting both the occurrence and absence of these error types in both the training data set and the cross-validation sample. However, for 'perceptual errors' and 'violations', in both data sets the NN performed much better when predicting that these categories of error *will not* occur (see table 4). In fact, the correct classification rates for the occurrence of these level 1 categories of unsafe act was quite low (between 11.4 and 24.7%). Nevertheless, the overall correct classification rate in these categories remained high at between 68.8 and 80.0% (table 3). The reason for this lies in the discrepant rates of the observation of errors in these two categories. In both instances, the frequency of observation of 'perceptual errors' and 'violations' was relatively low, hence a high correct prediction rate of 'error not observed', resulting in a high overall correct prediction rate (tables 3 and 4). It will be noted that in the case of the presence or absence of 'decision' and 'skill-based errors', the rates of occurrence and non-occurrence were somewhat closer.

Examining the performance of the NN from a signal detection perspective, the SI results in table 6 (which provide an overall index of how well the model performs when making correct predictions – 'hits' and 'correct rejections' versus incorrect predictions - 'misses' and 'false alarms') suggests that it performs well for decision-errors and skill-based errors. The SI results are for 'decision' and 'skill-based errors' are at the upper end for Human Factors predictive techniques (Stanton, Salmon, Rafferty, Walker, Baber & Jenkins, 2013; Stanton and Stevenage, 1998) and even those for ‘perceptual errors’ and ‘violations’ are of a similar order to the values observed in other contexts (e.g. Stanton, Salmon, Harris, Marshall, Demagalski, Young, Waldmann & Dekker, 2009).

HFACS has been subject to criticisms by several authors suggesting that the framework has only a weak link between the working environment and human error and that it merely repositions human errors by shifting them from operations to higher levels in the organization, instead of finding solutions for them (Dekker 2001). Other authors (e.g. Leveson, 2011) have commented that HFACS is merely an extension of Heinrich’s (1931) ‘Domino Model’, predicated upon simple linear relationships between events proximal to the accident and those more organizationally remote and that it does not capture the complexity of modern operations where there may be many interacting, non-static factors preceding a failure. More recent accident models based on systems theory attempt to describe the aetiology of the accident by reference to the performance of the system as a whole, rather than as simple failures characterized as ‘cause and effect’ mechanisms (Hollnagel, 2004). However, NN models can begin to capture such complexity in systems. The result from the NN analysis can target the most influential input factors contributing to the unsafe acts, potentially resulting in effective remedial actions.

Although HFACS was based directly on the organizational theory of failure proposed by Reason (1990; 1997) at the time when it was first conceived there was little or no quantitative data to actually support the model. However, there are an increasing number of papers describing the statistical relationships between components at the different levels in the analysis and classification system giving increasing support to the underpinning theory behind the framework (Li & Harris 2006a; Li & Harris, 2006b; Li, Harris & Yu, 2008; Tvaryanas, Thompson & Constable, 2006). These analyses begin to describe statistically how actions and decisions at higher HFACS levels promulgate through an organization to result in operational errors and accidents. The NN described in this paper has taken these analyses further by developing an empirically derived, verifiable model of the relationship between HFACS level-2; Preconditions for Unsafe Acts; (Condition Tokens) and level-1; Unsafe Acts of Operators; (Unsafe Act Tokens). Although the relationship between the inputs and outputs from the NN is complex, it is also congruent with the model of human error developed by Reason (1990; 1997) upon which HFACS is predicated.

The work in this paper is limited in that it only addresses two levels in the HFACS model and uses a relatively small sample for an NN-based analysis. A larger sample would be beneficial to address the issues associated with sample size in the 'perceptual errors' and 'violations' categories which had a relatively large mis-classification rate when an outcome in these categories was involved. Further work now also needs to be undertaken to incorporate data from HFACS levels 3 and 4 into an NN-based analysis to provide an even richer model of the occurrence of unsafe acts at an operational level. Nevertheless, NNs offer a viable method of analysing complex, safety indicator data and relating it to multiple outcomes to produce an empirically testable model.

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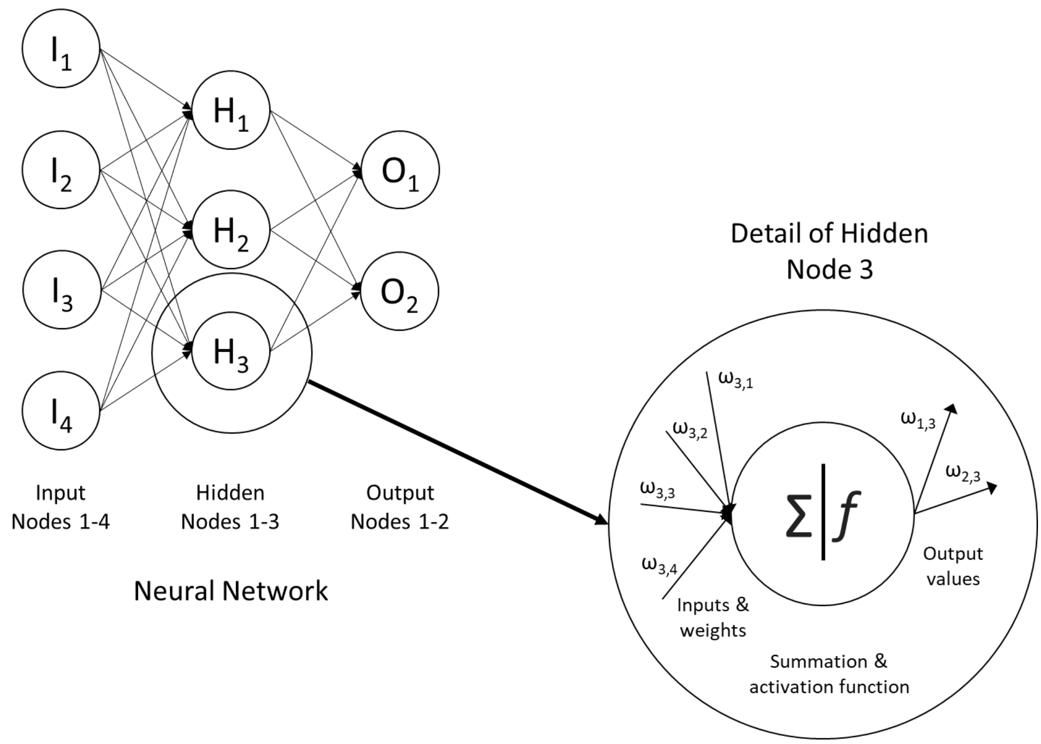

Figure 1 **Elements of the multi-layer perceptron type of NN (from Duggan & Harris, 2001; adapted from Hair, Anderson, Tatham & Black, 1998; and Garson, 1998).**

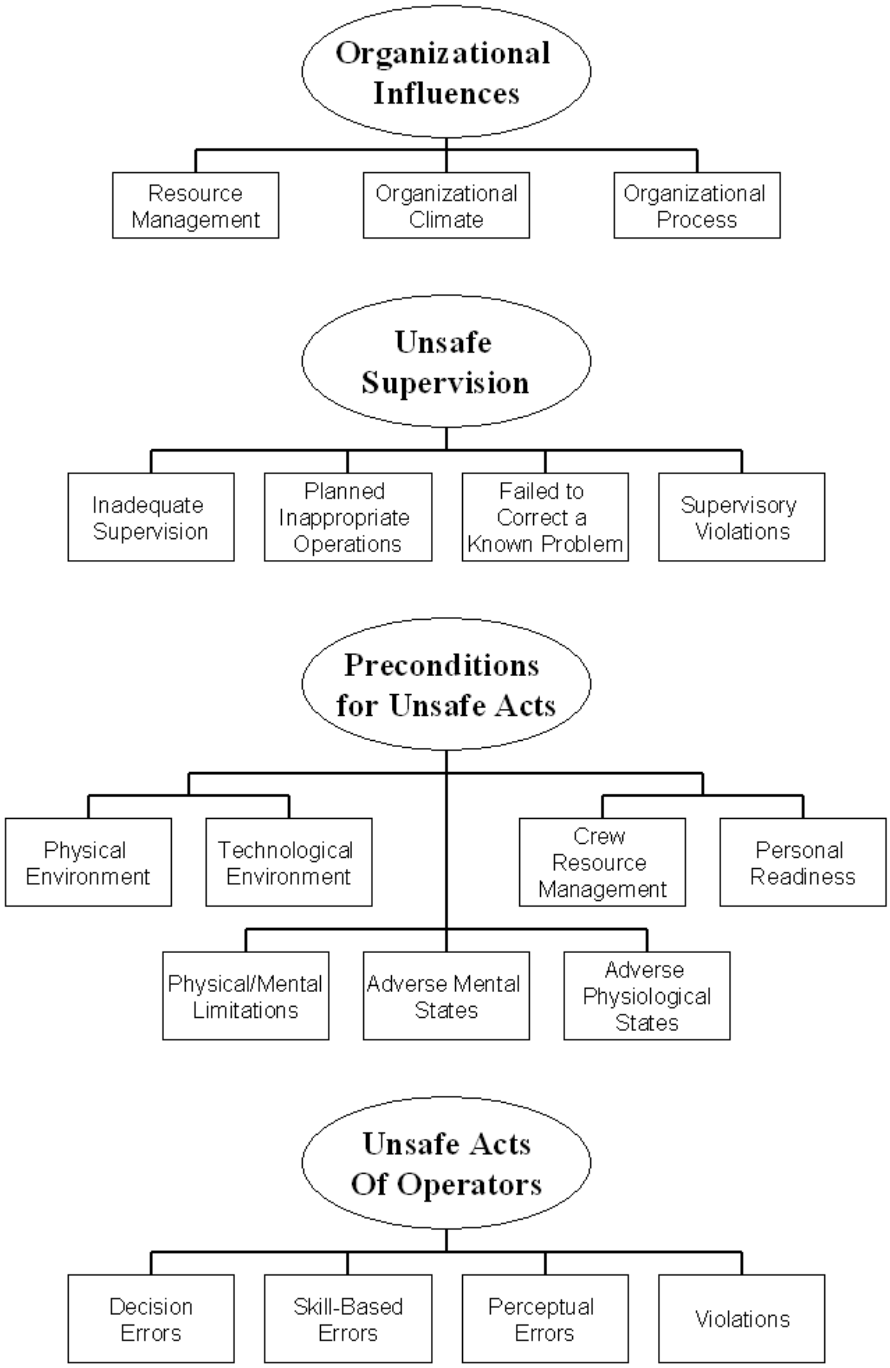

Figure 2 The original HFACS framework (Wiegmann & Shappell, 2003).

Table 1. Counts and inter-rater reliability statistics for each HFACS sub-category for all 523 accidents. Note that the percentages do not sum to 100% as more than one causal factor was associated with the majority of accidents. As a result of having a very low frequency of occurrence, the sub-category of 'Adverse Physiological States' was dropped from the subsequent analyses.

	HFACS Category	**Count**	**Percentage**	**% Agreement**
Level-2, Preconditions for Unsafe Acts (Condition Tokens)	Technology environment	44	8.4	89.9
	Physical environment	74	14.1	92.2
	Personal readiness	29	5.5	72.3
	Crew resource management	146	27.9	89.7
	Physical/mental limitation	73	14.0	90.4
	Adverse physiological states	*2*	*0.4*	*96.4*
	Adverse mental states	184	35.2	86.0
Level-1, Unsafe Acts of Operators (Unsafe Act Tokens)	Violations	160	30.6	84.9
	Perceptual errors	116	22.2	85.1
	Skilled-based errors	226	43.2	83.4
	Decision errors	223	42.6	81.5

Table 2 Weights on the paths from the input nodes (HFACS Level 2 ‘Preconditions for Unsafe Acts’) to the hidden nodes, and from the hidden nodes to the output layer (HFACS level 1 ‘Unsafe Acts of Operators’).

Parameter Estimates

Predictor		Predicted: Hidden Layer Node 1	Node 2	Node 3	Node 4	Node 5	Node 6	Node 7	Node 8	Node 9	Decision Error NO	Decision Error YES	Skill Based Error NO	Skill Based Error YES	Perceptual Error NO	Perceptual Error YES	Violation NO	Violation YES
Input Layer	(Bias)	.837	.334	-.890	-.521	.094	.306	.388	-.033	-.033								
	Adverse Mental State NO	-.625	.222	.629	-.828	-.518	.043	.352	-.139	-.139								
	Adverse Mental State YES	1.316	-.305	-.841	-.050	.273	-.195	-.083	.261	.261								
	Physical/Mental Limitation NO	-.894	.032	.327	.034	.501	-.295	.662	.716	.716								
	Physical/Mental Limitation YES	.869	.445	-.518	.440	-.524	.004	-.414	-.584	-.584								
	Crew Resource Management NO	-1.149	.310	.470	.297	.383	-.204	-.059	-.604	-.604								
	Crew Resource Management YES	1.414	.110	-1.119	-.317	-.432	-.230	-.285	-.146	-.146								
	Personal Readiness NO	-.207	-.146	.118	-.718	.088	-.030	-.166	.079	.079								
	Personal Readiness YES	.847	.135	-.803	.648	.156	.596	.004	-.071	-.071								
	Physical Environment NO	1.132	-.409	-.968	.423	.982	.764	.070	.298	.298								
	Physical Environment YES	-.047	.138	-.248	.238	-.368	.167	.316	-.730	-.730								
	Technology Environment NO	.781	.005	-.226	.431	.336	-.091	-.498	-.065	-.065								
	Technology Environment YES	-.348	.041	-.359	-.526	-.659	.166	.724	-.119	-.119								
Hidden Layer	(Bias)										-.081	-.645	.362	-.289	.346	-1.085	.779	-.450
	Node 1										-1.184	.772	-.705	.386	-.874	.461	-.271	.992
	Node 2										-.068	.689	-.516	-.046	.029	.141	-.011	-.002
	Node 3										.241	-.797	.211	-.525	-.055	.124	-.211	-.469
	Node 4										-.242	.322	.371	-.251	-.100	-.524	-.357	-.089
	Node 5										.229	-.144	-.317	.419	-.186	-.544	.435	-.028
	Node 6										.420	-.771	.274	-.480	.226	-.415	.486	-.458
	Node 7										-.137	-.238	.119	.325	.606	.283	-.452	-.235
	Node 8										-.349	.089	-.443	-.426	.460	-.286	-.411	.527
	Node 9										.307	-.824	.021	.091	-.146	.023	-.153	.098

Table 3 Model processing summary and overall output correct classification percentages.

Training	Cross entropy error		765.085
	Average percent correct predictions		74.2%
n=355 (69.7%)	Percent correct predictions for categorical dependents	Decision error involved	74.6%
		Skill-based error involved	72.7%
		Perceptual error involved	80.0%
		Violation involved	69.6%
Cross Validation	Cross entropy error		320.517
	Average percent correct predictions		73.4%
n=154 (30.3%)	Percent correct predictions for categorical dependents	Decision error involved	70.8%
		Skill-based error involved	76.0%
		Perceptual error involved	77.9%
		Violation involved	68.8%

Table 4 **Predictive accuracy of the NN (training and cross-validation samples) broken down by HFACS level 1 category.**

	Observed	Predicted No error (n)	Error (n)	Percent correct
	Decision error involved			
Training	No decision error involved	155	42	78.7%
	Decision error involved	48	110	69.6%
Cross Validation	No decision error involved	68	21	76.4%
	Decision error involved	24	41	63.1%
	Skill-based error involved			
Training	No skill-based error involved	141	57	71.2%
	Skill-based error involved	40	117	74.5%
Cross Validation	No skill-based error involved	65	20	76.5%
	Skill-based error involved	17	52	75.4%
	Perceptual error involved			
Training	No perceptual error involved	264	10	96.4%
	Perceptual error involved	61	20	24.7%
Cross Validation	No perceptual error involved	116	3	97.5%
	Perceptual error involved	31	4	11.4%
	Violation involved			
Training	No violation involved	218	16	93.2%
	Violation involved	92	29	24.0%
Cross Validation	No violation involved	101	14	87.8%
	Violation involved	34	5	12.8%

Table 5 **Relative importance of the predictor variables at HFACS level 2 ('Preconditions for Unsafe Acts') to the error categories at HFACS level 1 ('Unsafe Acts of Operators').**

	Importance	Normalised Importance
Adverse mental states	.159	65.8%
Physical/Mental limitations	.242	100.0%
Crew resource management	.203	83.8%
Personal readiness	.136	56.2%
Physical environment	.135	55.9%
Technological environment	.125	51.6%

Table 6 SI values for predictions derived from the cross-validation data set.

HFACS Level-1 (Unsafe Acts of Operators) category	Sensitivity Index
Violations	0.5032
Perceptual errors	0.5436
Skill-based errors	0.7592
Decision errors	0.6974

$$\mathrm{SI} = \left(\frac{\left(\dfrac{\mathrm{Hit}}{\mathrm{Hit} + \mathrm{Miss}} \right) + 1 - \left(\dfrac{\mathrm{False\ Alarm}}{\mathrm{FA} + \mathrm{Correct\ Rejection}} \right)}{2} \right)$$

Equation 1 Sensitivity Index formula (from Stanton & Stevenage, 1998)

Using neural networks to predict HFACS unsafe acts from the pre-conditions of unsafe acts

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