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A Conceptual Framework of Occupational Safety and Health Risk Management in Malaysia Shipyards Industry

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ABSTRACT

Occupational safety and health (OSH) risk management research is common in industries such as construction, chemical production, electrical and electronic production. However, to date there is a lack of research performed on the OSH risk management related to shipyard industry. OSH practitioners often carry out audits by identifying hazards, evaluating risks, and to do preventive decisions to manage the risks. The aforementioned task is difficult to execute due to multiple influencing factors that affect the decision-making and this replies on OSH practitioners' experience and knowledge. Thus, this paper reviewed a conceptual risk management framework which entails hazard identification, risk assessment, quantitative decision-making, risk control and ANN machine learning risk prediction. The framework methods were reviewed according to its characteristic, advantages, and disadvantages. The purpose of the review paper was to provide an overview of the methods' application, impact, and effectiveness in developing a continually improving risk management framework to lower the risk exposure level of workers in the shipyards industry.

1. Introduction

The global ship building industry has seen tremendous growth over the past several years because of the rising need for more transportation capacity, particularly in China, Japan, and Korea. In general, productivity and product quality are now significant factors in the competitiveness of the shipyard. Information technology, fabrication process flows, skilled labour, shipyard planning, and management are the main variables to improve the shipyard production chain. However, in order for the global shipbuilding industry to remain competitive, certain technology or managerial abilities are needed. For instance, China's shipbuilding benefits from a large, skilled labour, massive capital, and a stable ship building sector. The employment of qualified professionals has allowed Japan's shipbuilding industry to remain competitive, while Korean shipyards are mostly known for

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their expertise in managing dry docks [1]. Additionally, the process of producing ships is not only dependent on technological advancement and innovation but also on a more formalised organisation of labour, the capacity of the workplace, and simulation-based design for a shipyard production process [2].

On the other hand, Malaysia's ship building and ship repair (SBSR) industry is a significant contributor to the nation's Gross National Income (GNI) and is expected to provide 55,500 employments by 2020 [3]. Consequently, SBSR is crucial to the Malaysia's business expansion. According to data, there are over 100 shipbuilding businesses registered in Malaysia, 40 of which are based in Sibu, Sarawak [4]. This demonstrates how Malaysia's Sarawak state dominates shipyards and shipbuilding industries. According to the geographic analysis, most of the shipyards in Sarawak are located along the riversides instead of facing to an open sea. Literally, activities that are carried out in SBSR industry are considered under the monitoring of occupational safety and health (OSH) risk management. This is because most of the activity works are human capitalized.

Most shipyards have health safety environment management system (HSEMS) in place, however some are still incomplete. This is because heath safety and environment (HSE) issues were not given high attention, nearly 10% of shipyards lacked a clear HSE policy or risk management [5]. As a result, there is a lack of OSH commitment in the shipyard company’s management.

Besides that, many activities of fabrication works have been subcontracted. Subcontractors were fragmented into separate organizations that do not collaborate during the shipyards' fabrication process [6]. Therefore, subcontractors were poor to implement OSH awareness in the working surrounding. This has indirectly increased the workers' risk exposure at the shipyards. Without strict OSH management practiced in shipyards, a significant number of cases where workers were discovered suffering from lacerations, crushes, avulsions, fractures, amputations, or caught in hazardous situations and so on, have been documented [7].

In order to prevent the accidents from happening, site audit and investigation were carried out by the OSH practitioners to identify the significant hazards (hazard identification). Improvement was advised based on OSH practitioners’ experience and knowledge. However, previous research has shown that OSH practitioners have difficulties in risk analysis and making decision in the accidents [8]. In other words, due to varied opinions and varying degrees of expertise, it is determined that the reliability of risk level assessment (risk assessment) and the priority of making decision (quantitative decision-making) are inadequate.

Nevertheless, Sarkar *et al.,* [9] showed that risk control did not appear to be based on analytical data gathered from accidents. Data collected was not utilized to identify the contributing factor of accidents (risk control). In the other words, there is no data optimization to understand the root cause and the accidents continue to occur in the shipyard sector (risk prediction) [9].

As a result, the review paper studies a conceptual framework that works well in the shipyards industry to solve the problem statements discussed. The formulated risk management framework shown in Fig. 1 entails potential hazards identification, risk assessment, quantitative safety decision-making, risk control, and machine learning risk prediction. It connects each other in forming a continuously improving risk management framework.

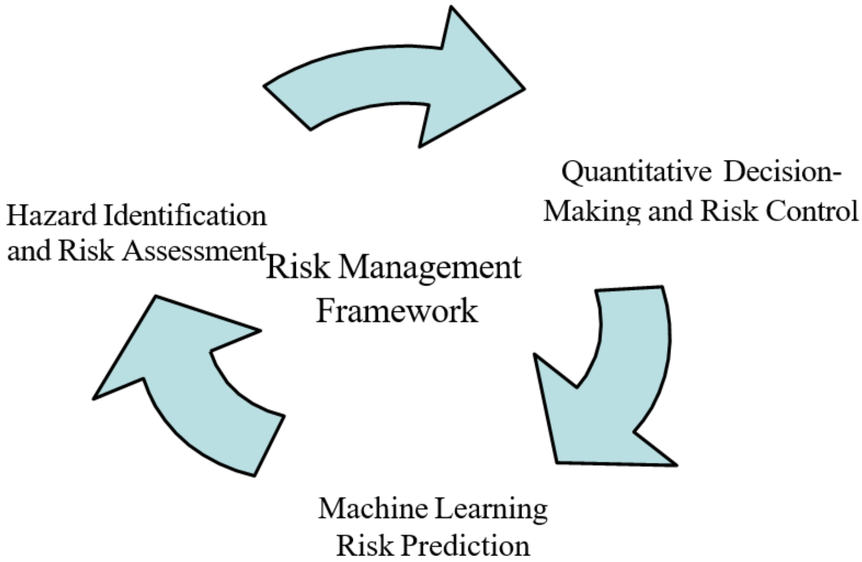

Fig. 1. Risk management framework

2. Specific Scope and Objective

Review paper aims to study a conceptual risk management framework according to its characteristic, application, advantages, and disadvantages. The objectives of the conceptual framework aim to achieve the following goals:

1. To identify potential hazards and assess risks exposure at the shipyard.
2. To evaluate a risk control for shipyards based on the quantitative safety decision-makings.
3. To integrate the ANN machine learning risk prediction technique into the formulated conceptual risk management framework.

3. Risk Management Conceptual Framework

3.1 Hazard Identification Methods

In risk management framework, hazard identification method has been proposed either offline or online to identify and examine any circumstances that can endanger the environment, human safety, or property and result in a substantial financial expenditure.

Paik *et al.,* [10] explained that hazard identification (HAZID) was considered as a qualitative identification method and widely used in general offshore installation works. It was used to identified hazards thoroughly in all categories such as physical, chemical, biological, ergonomic, and psychosocial in the process activity. For example: falling object, heavy lifting, gas leaking, explosion, oil spilled and so on. However, it is time consuming to list down all the identified hazards [10].

Besides that, hazard and operability (HAZOP) was studied by Anderson [11] to identify hazards in a systematic and thorough manner by taking all hazardous processes into account. Though it was widely used in a list of significant issues which is able to present dangers or operability issues [11].

On the other hand, Rahmat *et al.,* [12] investigated the use of Fault Tree Analysis (FTA) method for hazard identification, which involved the logical synthesis of numerous basic events. FTA was applied as a top to down strategy to determine all probable reasons of system failure down to a single critical failure [12].

The application of event tree analysis as a logical representation of various events that followed a primary event or basic event has also been demonstrated and shown by Hong *et al.,* [13]. This technique proved beneficial for connecting an event to other consequence model criteria, such as design standard, age, historical performance, degradation, the gap between inspections, and more. However, it was limited to one initiating event with various risk consideration [13].

Other than that, failure mode effects analysis (FMEA) is also a quantitative technique that has been frequently applied in engineering projects to investigate potential failure modes and eliminate prospective failures during system designs. In particular, it focuses on the primary failure mode and offers both quantitative and qualitative measurements to implement remedial actions. It has been proven in many areas such as vehicles, electronics, consumer goods, manufacturing facilities, and telecommunications. However, Chang *et al.,* [14] proved that FMEA method was used to evaluate risk on a single failure. It did not solve the problem for two or more contributing factors to the failure at the same time [14]. Table 1 shows the comparative summary of different hazard identification methods with their application characteristic, advantages, and disadvantages.

Table 1
Comparative summary of different hazard identification methods

Author	Type of Hazard Identification	Characteristic	Advantages	Disadvantages
Anderson [11]	HAZOP	Hazard and Operability (HAZOP) is useful to identify all hazardous process in a systematic and thorough manner.	Widely used in a list of significant issues which is able to present dangers or operability issues. Widely used in a list of suggestions, activities, or modifications to improve safety or operations.	Requires time consuming to list down all the process activity.
Paik *et al.,* [10]	HAZIP	Hazard Identification (HAZID) has been studied for the general offshore installation. HAZID is mostly used in the processing industry.	A thoroughly hazard identification in all categories such as physical, chemical, biological, ergonomic, and psychosocial in the process activity.	Requires time consuming to list down all the identified hazards.
Rahmat *et al.,* [12]	FTA	Fault Tree Analysis (FTA) is a quantitative method that logically combines a number of minor events that contribute to a major top event. FTA is a top-down strategy to find all potential root causes of system failure.	A collection of logic diagrams which shows the relationships between different failures, mistakes, and accidents.	Quantification requires a significant calculation in combination of few risk evaluations.
Hong *et al.,* [13]	ETA	Event Tree Analysis (ETA) is a quantitative approach that logically represents many occurrences that happen after an initiating or fundamental event. It has been proven beneficial for connecting an event to other consequence model criteria, including design standard, age, historical performance,	A set of logic diagram that illustrates the sequence of events in specific accidents. Widely used in all design phase, facility modification and operation	Limited to one initiating event with various risk consideration.

		degradation, the gap between inspections, and more.		
Xiao *et al.,* [36]	FMEA	Failure Mode Effects Analysis (FMEA) is another quantitative or qualitative method which is an excellent analytical tool. It has been widely used in engineering projects to investigate potential failure modes and eliminate prospective failures during system designs.	A list of equipment used in facilities. It shows the possibility method of failure as well as the consequences of those failures for the facility's equipment.	Technically, it is only able to evaluate the possibility of impact based on single failure.

3.2 Risk Assessment Methods

Risk assessment is a combination of few input parameters that make it possible to evaluate the risk at the various hazardous situations. With this, high-risk and low-risk situations can be immediately distinguished from one another.

Risk assessment was categorised by *Shaleh et al.,* [15] as a quantitative technique with a minimum of two parameters. The degree of injury, while also known as a consequence, was represented in a single parameter. The other parameter represented the probability of occurrence that harmed. Rather than using probability, some techniques employed chance, frequency, or likelihood. The quantitative technique was used to calculate the frequency of a specific hazardous occurrence with respect to time. Risk assessment Table 2 and Table 3 at each production process was calculated as the following:

$$R = L \times S \tag{1}$$

Where:
R is the risk;
L is the probability of risk, and;
S is consequences of risk occurrence.

Table 2
Indication of Likelihood [15]

Likelihood (*L*)	Example	Rating
Most likely	The most likely outcome of the event or threat coming to pass	5
Possible	Has a reasonable probability of happening and is not uncommon	4
Conceivable	Perhaps at some point in the future	3
Remote	Has not been documented to happen in many years	2
Inconceivable	Is essentially unattainable and has never happened	1

Table 3
Indication of Severity [15]

Severity (*S*)	Example	Rating
Catastrophic	Cause of many deaths, and irreversible property damage	5
Fatal	Cause of a single death if the danger happens, significant property damage	4
Serious	Permanent impairment, non-fatal injury	3
Minor	Disabling but not permanent injury	2
Negligible	Minor abrasions, bruises, cuts, first aid type injury	1

On the other hand, according to Samekto *et al.,* [17], three variables were discovered for having an impact on the likelihood of an event occurring. Namely, the maturity factor (*Pm*), which reflected the likelihood of risk related to the development of new technology; the complexity factor (*Pc*), which reflected the likelihood of risk related to the development of systems; and the dependency factor (*Pd*), which reflected the likelihood of risk related to dependence on facilities, contractors, and other factors. The consequence of risk occurrence was also affected by three factors, they were performance, cost, and schedule respectively [16].

Moatari *et al.,* [18] also prescribed that the risk exposure Eq. (1) of people were included with both frequency and duration of exposure. This research was based on four- parameters categorization for probability of occurrence of harm (*Ph*). Eq. (2) and Eq. (3) were developed, shown in Table 4, Table 5, Table 6, Table 7 and Table 8:

$$R = S \times Ph \tag{2}$$

Where:
R is the risk value;
S is the severity of harm, and;
Ph is probability of occurrence of harm.

$$Ph = Exf + Exd + [2 \times Pe] + A \tag{3}$$

Where:
Ph is the probability of occurrence of harm;
Exf is the frequency of exposure to the hazard;
Exd is the duration of exposure to the hazard;
Pe is the probability of occurrence of a hazardous event, and
A is the possibility of avoidance.

Table 4
Severity of Harm [17]

Severity of Harm (*S*)	Rank
Minor wounds (bruises) that do not need first aid or minor wounds that do but do not take longer to heal.	1
Accidents involving more than first aid, lost time, irreparable damage, and minor disabilities but allowing the worker to resume their job	2
A serious impairment, with the possibility that they would not be able to return to their previous position.	3
The individual is rendered permanently disabled and is unable to work.	4
One or more fatalities	5

Table 5
Frequency of Exposure to Hazard [18]

Frequency of Exposure to the Hazard (*Exf*)	Rank
Less than once per year	1
Annually	2
Monthly	3
Weekly	4
Daily to continuously, i.e. several times per hour	5

Table 6
Duration of Exposure to Hazard [18]

Duration of Exposure to the Hazard (*Exd*)	Rank
< 1/20 of work time	1
1/10 of work time (45 min per 8 h shift)	2
1/5 of work time (90 min per 8 h shift)	3
Half of work time (1/2) (4 h per 8 h shift)	4
Continuously during work time	5

Table 7
Probability of Occurrence of a Hazardous Event [18]

Probability of Occurrence of a Hazardous Event (*Pe*)	Rank
Negligible	1
Unlikely	2
Possible	3
Likely	4
Significant	5

Table 8
Possibility of Avoidance [18]

Possibility of Avoiding or Limiting the Harm (*A*)	Rank
Highly significant	1
Significant	2
Somewhat likely, with some conditions	3
Unlikely	4
Nil	5

Besides that, Anderson [11] studied on risk analysis in industrial machines design and installation and explained that risk evaluation diagram was covered with the parameters of severity (*S*), avoidance (*Av*), probability of event reoccurrence (*Pr*), frequency of risk reduction (*Fr*). This is shown in Eq. (4). Moreover, risk evaluation diagram was further evaluated into details that covered the parameters of severity (*S*), avoidance (*Av*), probability of event reoccurrence (*Pr*), frequency of risk reduction (*Fr*), shown in Figure 2.

$$R = SDiagram(Av + \mathrm{Pr} + Fr) \tag{4}$$

Where:
R is the risk value;
S is the severity;
Av is the avoidance;
Pr is the probability of event reoccurrence, and;
Fr is the frequency with the life phase of risk reduction.

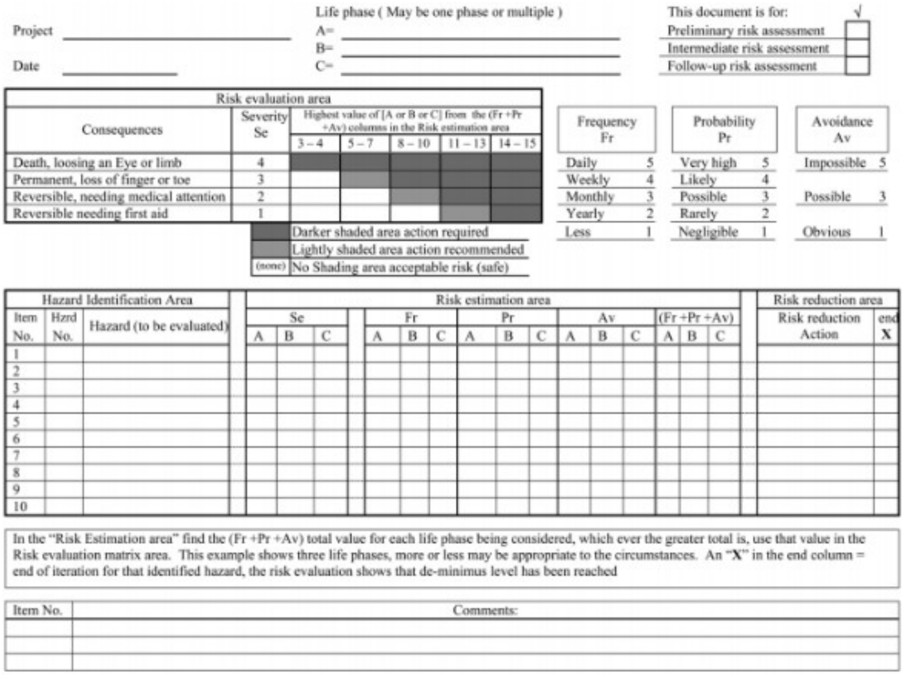

Fig. 2. Risk Evaluation Checklist Diagram [11]

Table 9 gives a summary of comparison between different risk assessment methods at its application, advantages and disadvantages that is in line with the conceptual risk management framework.

Table 9
Comparative summary of different risk assessment methods

Author	Risk Assessment Formula	Advantages	Disadvantage
Anderson [11]	$R = SDiagram\left(Av + \Pr + Fr\right)$ Where: R is the risk value; S is the severity; *Av* is the avoidance; *Pr* is the probability of event reoccurrence, and; *Fr* is the frequency with the life phase of risk reduction	A quantitative risk estimation tool which has converted the likelihood into the parameters of avoidance and probability of event reoccurrence.	Requires a diagram on hand for referring to the diagram on risk estimation.
Shaleh *et al.,* [15]	$R = L \times S$ Where: R is the risk; L is the probability of risk, and; S is consequences of risk occurrence.	A quantitative approach and it is simple to understand. Widely used in general industries under Malaysia guideline.	Requires a large amount of historical information for example seriousness of severity and frequency of the likelihood.
Moatari-Kazerouni *et al.,* [18]	$R = S \times Ph$ Where: R is the risk value; S is the severity of harm, and; *Ph* is probability of occurrence of harm	A quantitative approach and it is developed from equation R = L x S which has taken the occurrence of harm into consideration. It is similar to the other risk estimation tools. It covers different areas of	It is a bit complicated and requires a mathematical calculation tool.

$$Ph = Exf + Exd + [2 \times Pe] + A$$ Where: *Ph* is the probability of occurrence of harm; *Exf* is the frequency of exposure to the hazard; *Exd* is the duration of exposure to the hazard; *Pe* is the probability of occurrence of a hazardous event, and *A* is the possibility of avoidance	OSH. It defines details in parameters.

3.3 Quantitative Safety Decision-making

Once the risk assessment is done, risk level and priority of risk control are evaluated. Risk level evaluated in term of risk matrix is shown in Figure 3 and Table 10.

Lee [19] explained that OSH practitioners made decisions based on the results of site audit inspection and past experience of identifying risk with comparable significant conditions, but it was a challenging process because many elements were influencing the prediction. Once the level of risk exposure was determined, measurement was necessary since risk acceptance was deemed manageable. The risk acceptance was demonstrated using the risk matrix approach (risk level indication), which included the likelihood that damage would occur and the severity of harm. Lee [19] also pointed out that risk matrix had been commonly applied in general industries. This can refer to the guideline of OSH regulation in Malaysia.

	Severity (S)				
Likelihood (L)	1	2	3	4	5
5	5	10	15	20	25
4	4	8	12	16	20
3	3	6	9	12	15
2	2	4	6	8	10
1	1	2	3	4	5

Table C

High
Medium
Low

Fig. 3. Risk Matrix [19]

Table 10
Risk level evaluation [19]

Risk	Description	Action
15-25	High	As a detail in the hierarchy of controls, a HIGH risk necessitates quick action to control. The risk assessment form requires that all actions done be recorded, along with a completion date.
5-12	Medium	A MEDIUM risk necessitates a plan for risk mitigation that, if needed, includes temporary steps. The risk assessment form has to have a record of the actions done, along with a completion date.
1-4	Low	It would be acceptable to accept a LOW risk, and no further decrease would be necessary. However, if the risk can be managed quickly and successfully, a control measure has to be implemented and recorded.

Besides that, risk level can also be evaluated in risk graph, and quantified risk assessment (QRA) which are prescribed according to the indicator method. Nait-Said *et al.,* [20] studied on the method of risk graph to measure the level of safety integrity when the safety equipment is in place.

However, risk graph method is a complex as it requires skill graph reader to identify the risk level [20].

Moreover, Buyong *et al.,* [21] evaluated quantified risk assessment (QRA) as quantitative method that showed in mathematical calculation [21]. This serves to illustrate the probability that a certain event will transpire over a given amount of time. The yearly frequency of an individual's death was frequently used to describe the risk. As a result, QRA made it possible to compare the projected risk with parameters that may be linked to annual information on accidents or fatalities. Small number was used to express risk such as 1.54×10^{-4}, that is able to provide a high-precision imprint. The advantage of QRA was that a high precision number of risks can be indicated the achievement in health and safety. From there, a comparison can be done on the effectiveness of decision-making in risk management within a duration of time.

Furthermore, quantitative safety decision-making is performed in risk priority number (RPN) to evaluate the priority of risk control implementation. In other words, higher risk assessment shows the more significant of safety decision- making in preference with good detection of risk control. Chang *et al.,* [14] explained the three-factor parameters mentioned in RPN, were origin from FMEA and they were evaluated as severity (*S*), occurrence (*L*), and detection (*D*) as shown in Eq. (5).

$$RPN = S \times L \times D \tag{5}$$

RPN method had been widely used in engineering-based risk analysis. All parameters were examined and assigned with RPN value. An excellent detection (D) of current practiced risk control shows the lowest in RPN. However, an undetectable risk control shows the highest in RPN. This explains that current practiced risk control is not practicable and has the priority to be improved. In other words, corrective action is implemented by considering the highest RPN value down to the least. The intention of the corrective action is to eliminate or minimise the critical failure mode.

Table 11 shows the summary of comparison of risk priority methods at their application, advantages, and disadvantages.

Table 11
Comparative summary of different risk priority methods

Author	Risk Priority Method	Application	Advantages	Disadvantages
Nait-Said *et al.,* [20]	Risk Graph	Risk Graph is used to identify the safety integrity level for safety instrumented functions. The tree structure of the risk graph is working from the left to the right.	Encourage thorough discussion of the hazards and risks. Provide risk prioritization.	A quantitative and qualitative method which is a bit complex, and it requires skill graph reader to identify the risk level.
Chang *et al.,* [14]	Risk Priority Number	Three-factors of Risk Priority Number (RPN) in FMEA stands for severity (S), occurrence (L) and detection (D). $RPN = S \times L \times D$ RPN method is widely used in engineering analysis. Once all items have been examined and assigned with a RPN value, an appropriate corrective action is implemented by considering the highest RPN value down to the least.	A quantitative and qualitative method which shows the priority of risk reduction and it is easy to understand. The intention of the corrective action is to eliminate or minimize the critical failure mode, which displays the highest severity, most frequent occurrence,	RPN results are subjective due to personal perception of rating in severity, occurrence, and detection.

			and lowest detection ranking.	
Lees [19]	Risk Matric	Risk Matrix is a multidimensional table of risk level indication which allows the combination of any class of harm's severity with any class of probability of occurrence that harm. It can be referred to the guideline of the OSH regulation in Malaysia.	A qualitative method and easy to understand and most used in general industries. Risk assessment for supporting to the risk evaluation.	The lack of depth is an issue because should the tool be used as the only method of risk evaluation; the intricacies of the hazard could be oversimplified.
Buyong *et al.,* [21]	Quantified Risk Assessment	A quantitative approach that uses calculation to determine the likelihood of a particular result occurring over time, as precisely as possible given the data at hand. In general, risk is often expressed as the annual frequency of the death of an individual, for example: 1.54×10^{-4}.	High precision number of risks to indicate the achieved goal in health and safety. Comparison can be done on the effectiveness of decision-makings in risk management which is carried out within a period of time.	In general, the value only indicates the frequency of the death of an individual.

3.4 Risk Control

Based on the quantitative safety decision, risk control is implemented to prevent and reduce either a single element risk or multiple elements risk. Card *et al.,* [8] showed that risk controls in general were categorized according to the hierarchy chart shown in Figure 4. The hierarchy chart entails removal, replacement, technical management, management of administration and individual safety protection, is referred to the National Institute for Occupational Safety and Health (NIOSH) risk control version.

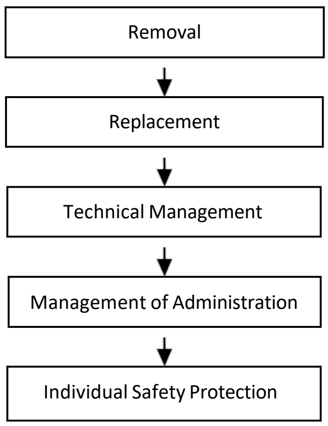

Fig. 4. Hierarchy of Risk Control

3.5 Risk Prediction

Prediction method in term of ANN machine learning has been proven in various fields, such as die cast's shrinkage prediction in engineering [22], analysis of stream flow trend and rain flow trend under environmental prospects [23], construction's capital forecasting [24], and it yielded very useful results [25]. However, to the authors' knowledge, literature review showed that occupational accident risk analysis had only demonstrated the use of ANN in terms of their predictive and explanatory capacities, with limited details on the data optimization to find out the root cause of workplace accidents [26-29]. Hence, ANN technique in various types of algorithm architecture is developed to perform a good risk prediction model.

In medical line, a study has been done on ANN model application of heart disease risk prediction. Yazdani *et al.,* [30] explained in details that Levenberg-Marquardt (trainlm) backpropagation algorithm was carried out with training, validation, and testing from a data set of 297 samples. The experiment was conducted using several training algorithms, including Resilent backpropagation (trainrp), BFGS Quasi-Newton backpropagation (trainbfg), and scaled Conjugate Gradient backpropagation (trainscg). 6 samples with missing values were removed as part of the data pre- processing step, and 13 data set descriptions of inputs were converted into encodings to be used as an input for the ANN model. The results showed the heart disease risk prediction. With the architecture of input neurons, a number of hidden neurons layers and output neurons were consisted of 13-30-1. 297 data were extracted to 80-10-10 for training-validation- testing. The architecture was able to achieve 100% accuracy performance, 100% sensitivity, 100% precision, and 100% specification based on the empirical findings. The architecture used the hyperbolic tangent sigmoid activation function (tansig) for the hidden layer and log-sigmoid activation function (logsig) for the output layer. This facilitated doctors to forecast the likelihood of heart disease [30].

On the other hand, Nassiri *et al.,* [31] reviewed accident prediction methods in traffic management. Evaluation was implemented by developing two types of the model, namely count regression and machine learning, to predict the number of crashes and severity of the crashes. Negative Binomial Regression (NBR) and Zero Inflated Negative Binomial Regression (ZINBR) models were the most common types of count regression to model accident frequency. On the other hand, Support Vector Machine (SVM) and Back-Propagation Neural Network (BPNN) were the most well-known supervised machine learning paradigms. The models' ability to forecast outcomes was assessed by computing error values. In order to create accident prediction models, analysis was done on data from 185 segments of traffic incidents that occurred in Mashhad, Iran, in 2007. The training was calibrated using 130 highway segments, or 70% of the data for those segments. The remaining thirty percent (55 highway segments) of the data were used to evaluate the testing models' prediction accuracy and calculate error values. The hyperbolic tangent function was used as the activation function, which had a greater range than other common functions. The numbers of epochs, the learning rate, and the momentum for the training process are set to 1000, 1, and 0.7, 17 neurons hidden layers were used to train the BPNN model, yielding performance results of 97.02% accuracy, 39.98% mean square error (MSE), 2.98% mean absolute error (MAE), and 6.32% root mean square error (RMSE). In contrast, 18 neurons hidden layers were used to achieve performance results of 95.85% accuracy, 31.43% MSE, 4.15% MAE, and 5.61% RMSE [31]. Comparison findings demonstrated that the BPNN model was the most successful model for forecasting the number of accidents, due to its low prediction and fitting error values. However, discussion revealed that, ANN technique had a black box structure without an analytical foundation. It required a time-consuming computational effort to minimize the over-fitting issues especially when the sample size was small.

Besides that, ANN is also applied in construction project cost estimation which was covered in a previous research. Using historical data from 169 completed projects, El- Sawalhi *et al.,* [32] created an ANN model for the prediction of the overall structural cost of construction projects in the Gaza Strips. The data were randomly divided into three groups. Namely, 69% for training, 16% for performance validation, and 15% for a completely independent evaluation of network generalisation. The eleven parameters that make up the input components are as follows: project type; number of stories; typical floor space; foundation type; slab type; number of elevators; exterior finishing type; air conditioning type; tilling type; electrical type; and sanitary type. Finally, specifying the desired parameter (output) which was the total cost of the project. The Multilayer Perceptron (MLP) comprised an input layer with 11 input neurons, a hidden layer with 22 hidden neurons, and an output layer with one output neuron. The architecture with Tanh transfer function and Momentum learning rate, which was part of the backpropagation algorithm, was carried out by utilising the total cost. By reviewing this research, the result of ANN in cost estimation performance was summarized as accuracy performance, AP 94%; mean absolute percentage error, MAPE 6%; mean square error, MSE $ USD 33,757; and correlation coefficient, R 0.995 [32].

Estimation of productivity in the management of construction projects has also been applied with the ANN method. This is because the quality of construction management is depending on the accurate estimation of the construction productivity. Al-Zwainy *et al.,* [33] developed an ANN model network by utilising the historical data from 150 data projects, 25% went towards performance validation, 60% went towards training, and 15% went towards computation. The labour productivity of marble finishing work for floors was estimated using this network. Data from residential, commercial, and educational projects in various regions of Iraq were used in the study to train the model and assess its effectiveness. A hyperbolic tangent sigmoid function was employed as the transfer function. The ANN model was used to forecast productivity using ten influencing factors, including age, experience, the number of assist labour, the height of the floor, the size of the marble tiles, security conditions, the health status of the work team, the weather, the condition of the site, and the availability of construction materials. The productivity of marble finishing work for floors was then predicted using a model. With a coefficient of correlation (R) of 89.55%, an average accuracy percentage (AP) of 90.9%, and a mean absolute percentage error (MAPE) of 9.1%, it was discovered that ANN can estimate productivity for finishing activities with a very high degree of accuracy. Hence, backpropagation neural network (PBNN) model has proven very successful in modeling nonlinear relationships [33].

In terms of risk forecasting in various applications, many artificial intelligence-based modeling has been employed as well ranging from mathematical, statistical, and simulation techniques. Odeyinka *et al.,* [34] reviewed and modelled the variation in the actual and expected cost flow resulting from construction's inherent risks. Data was obtained through a questionnaire survey and empirical data collection. The impact of risk variables on the cost flow projection was then investigated by obtaining data on the difference between the projected and actual cost flow from completed construction projects. The cost flow risk assessment model was developed utilising the neural network and the backpropagation method. The developed model was tested on 20 brand-new projects with satisfactory predictions of variations between the forecast and actual cost flow at 30%, 50%, 70%, and 100% completion stages. A cost flow risk assessment model was developed using 40 of the 50 data sets collected from the questionnaire survey. The remaining 10 data sets and the additional 10 data sets obtained from a construction business were used for the model's testing and validation. Neural network's inputs were associated with the 11 identified major risk variables through the questionnaire scores. Number of input data and output data also demonstrated that 11 input neurons and 4 output neurons were a good network architecture to start with. After a number of trials and errors, the network was found to be stabilized with 12 hidden nodes with a sigmoid transfer function. Thus, the result obtained was respectively error square, R^2 = 0.626 (30%), R^2 = 0.748 (50%), R^2 = 0.653 (70%) and R^2 = 0.767 (100%) with actual cost flow at 30%, 50%, 70% and 100% completion stages. And the relative Mean Absolute Deviation measured for the 20 new projects varies from Project No. 8 (0.067) to Project No. 7 (1.158). This showed that Project No. 7 had the least error prediction and was the nearest to the actual risk prediction cash flow [34].

Besides that, there is another research done on comparison between ANN, Support Vector Machines (SVM), and Decision Tree (C5) in the prediction of risk factors for diabetes cases. Barakat *et al.,* [35] developed a prediction model based on 500 nondiabetic and 268 diabetic data. The variables used as input risk factors included age, body mass index (BMI), triceps skinfold thickness, 2-hour serum insulin, diastolic blood pressure, and OGTT plasma glucose levels. The output class was binary (meaning the subject tested positive or negative for diabetes). Architecture 8-1-1 Quasi-Newton was developed and trained in ANN, SVM and C5 model according. Performance result showed that ANN training accuracy performance 83% and precision 82%; SVM training accuracy performance 83% and precision 87%; and C5 training accuracy performance 87% and precision 88% [35]. The research showed that the result of training accuracy in ANN and SVM were very much consistent and suggested that C5 be carried out based on the training data generated by ANN and SVM classifier to show the significant risk factors that contributed to the diabetes diagnosis.

Table 12 shows a summary of the comparison between different ANN architectures and algorithms at their application and performance for reference.

4. Discussion and Findings

The review paper limited to conceptual risk management framework at shipyards whereas activities of shipbuilding and ship repairing are carried out. Under the definition of the Factory and Machinery Act 1967, shipyard is defined as an industrial factory with the combination of office building, warehouse, workshops, dry dock area, wet dock area, and wharf. These are different utilization from other commercial wharves or personal jetties, for instance, speed boat jetty, cruise wharves, bay wharves, international or local ports, and so on where shipbuilding and ship repairing activities cannot be done. In addition, SBSR operations are carried out under the direction of manpower because most fabrication works are human capitalised. Therefore, this review paper only discusses workplace accidents, property damaged, and study on conceptual risk management framework at shipyards.

Many researchers have done the study on the typical risk management such as method of hazard identification, risk assessment, quantitative decision-making and risk control in other general industry such as chemical production [36], international port [37], and so on but the application of typical OSH risk management in shipyard industry still requires a room of improvement. These applications are depending on the OSH practitioners' experience and knowledge to analysis risk exposure level and prevent the accidents from happening. Thus, a review paper on ANN machine learning risk prediction are integrated into formulating the conceptual risk management framework. Review paper found out that architecture algorithm in construction study is suitable in analyzing the risk prediction in shipyards industry. Input-output paired wise of HSE factors in construction is similar in shipyards industry. Activities in construction such as working at height, scaffold erection, hand-tools handling, working under awkward posture, and weather exposure are almost identical in the shipyard's activities. These similar HSE contributing factors are relevant to identify the optimization patterns in predicting risk exposure at shipyards.

5. Conclusion

In this paper review, the formulated conceptual risk management framework on reducing the accidents at shipyards, is discussed. It stands for potential hazards identification, risk assessment, quantitative safety decision- making, risk control, and risk prediction.

Hazard identification has been proven to examine the awareness of shipyard management to identify potential hazards and common physical hazards that affect in the fabrication process. Following that, risk assessment is able to assess the risk level of each fabrication process, such as welding, lifting materials, sand blasting, and working at confined space, have common physical hazards (objective 1). Next, quantitative safety decision-making and risk control have been carried out to standardize the priority to make decision on risk control, and risk prevention. In this stage, it applies and strengthens the knowledge and experience of the management to improve and prevent occupational accidents from happening. The detection of risk control is considered in the sequence of safety decision-making in terms of the risk priority number (RPN). RPN is applied to improve decision- making for a clearer option, and method to prevent the accident from happening. This goes on with elimination, substitution, engineering control, administration, and personal protective equipment engagement in sequence (objective 2).

Following that, ANN with a supervised learning Back- Propagation Neural Network (BPNN) is discussed for output risk prediction. ANN architecture and algorithms were compared in several variables, and their interrelationships between independent and dependent variables for risk prediction (objective 3).

Therefore, the conceptual risk management framework that stands for potential hazards identification, risk assessment, quantitative safety decision-making, risk control, risk prediction is formulated to become a continuously improving risk management framework that suits to shipyards industry.

Table 12
Comparative summary of different ANN architectures and algorithms.

Author	Research Objective	Type of Model	ANN Architecture	Performance Measurement	Application
Odeyinka *et al.,* [34]	Estimation of cash flow risk assessment for 20 new projects	Multi-Layer Perceptron	• Feedforward Back Propagation Algorithm • 80% training, 10% validation, 10% testing • Four Layers • Sigmoid Transfer function • 11-12-4	R^2= 0.626 (30%), R^2= 0.748 (50%), R^2= 0.653 (70%) R^2= 0.767 (100%) with actual cost flow respectively. And the least relative Mean Absolute Deviation measure Project No. 8 (0.067) Highest relative Mean Absolute Deviation Project No. 7 (1.158).	Result from testing and validating data for 20 other building projects shows that an artificial network model could be useful in mapping and modeling the complex interaction between risks in construction and the usual variation observed between the forecast and the actual cash flow.
Barakat *et al.,* [35]	Prediction of risk factor for diabetes cases	Multi-Layer Perceptron	• Quasi Newton algorithm • Single layer • 8-1-1	And ANN training AP 83% and precision 82%. SVM training AP 83% and precision	Comparison is done between SVM, ANN and Decision Tree (C5). Decision Tree (C5) is carried out on the training data generated

				87%. C5 training AP 87% and precision 88%.	by ANN and SVM classifier to show the significant risk factors that contributed to the diabetes diagnosis.
Al-Zwainy *et al.,* [33]	Estimation of the labor productivity construction projects	Multi-Layer Perceptron	• Feedforward Back Propagation Algorithm • 60% training, 25% validation,15% testing • Single Layer • Transfer function hyperbolic tangent sigmoid • 10-1-1	AP = 90.9% MAPE = 9.1% R = 89.55% R^2 = 80.19%	The backpropagation neural network (BPNN) model is proven in modeling nonlinear relationships. Therefore, ANNs can be used instead of statistical programs to show the nonlinear function for any problem.
Nassiri *et al.,* [31]	Roadway accident number of crash and prediction severity of crash.	Multi-Layer Perceptron	• Feedforward Back Propagation Algorithm • Single Layer • 70% training. 30% testing. • Transfer function hyperbolic tangent is used as the activation function • Numbers of epochs, learning rate and the momentum of the training process are set to 1000, 1 and 0.7, • Comparison data set with 17 neurons layer and 18 neurons layer. • Comparison of prediction was done between NBR, ZINBR, SVM and BPNN	ANN 17 neurons hidden layer AP 97.02%, MSE 39.98%, MAE 2.98%, RMSE 6.32% ANN 18 neurons hidden layer AP 95.85%, MSE 31.43%, MAE 4.15%, RMSE 5.61%	BPNN model has the best prediction but does not have the best fitting among the trained models between NBR, ZINBR, and SVM. Disadvantage of ANN method is that these models has a black box form without an analytical basis, and it requires time consuming computational effort to minimize over-fitting issue especially when the sample size is small.
El-Sawalhi *et al.,* [32]	Total Cost Estimation in Construction Project	Multi-Layer Perceptron	• Feedforward Back Propagation Algorithm • 69% training, 16%validation, 15% testing • Single Layer • Transfer Function tanh • 11-22-1	AP = 94% MAPE = 6% MSE = $ USD 33757 R = 0.995	Questionnaire survey is used to identify the most effective parameters on building projects cost at the early stages of project.
Yazdani *et al.,*	Risk Prediction of Heart	Multi-Layer	• Feedforward Back Propagation	AP 100% Sensitivity 100%,	Comparison is done with different training

[30]	Disease	Perceptron	Algorithm • Single Layer • 80% training, 10% validation, 10% testing. • Different training function algorithms like trainscg, trainrp, trainlm, and trainbfg were carried out. • 13-30-1	Precision 100% Specification 100%	algorithms and transfer algorithms. It is concluded that target accuracy of 100% can be obtained by using trainlm algorithm with the architecture of 13-30-1.

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