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Hazards Risks in Manufacturing Industries: Possibility of Integrating Customized Needs

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Abstract

Manufacturing industries (Mrg-Inds) entails physically transformation of goods, with activities such as molding, cutting, and assembly, to final product. Hazards, associated with the activities in Mrg-Inds, are common among its workers. All the industries are face with tailored hazard risks and it is difficult to provide a common corrective measure. This study aimed at finding the possibility of integrating customized hazards in food, textile, chemical, leather and shoe, furniture and wood, and metal Mrg-Inds. The six industries assessed were located in Lagos and Ibadan, the southwestern part of Nigeria. Data were collected from 300 workers through questionnaire. Information related to peculiar types and prevalence of hazards in each of the industries were collected. Machine learning decision tree (Mld-tree) device, implemented in SPSS, was used to recognize the common hazards requiring the same decreasing measures. More than twenty-six hazards were collated from all the study areas. Chemical-related was rated (96.7%) major across the industries. This was followed by machinery-related (90%) and slips/falls (89%). The Mld-tree spotted hazards related with 'equipment' and 'ergonomics' as the first chance node and the most common across all the industries. The chance node was 'noise' derived when hazards related with 'equipment' was further splatted into end node. The study identified hazards connected with 'machinery', 'ergonomics' and 'noise' as the integrated hazards prevalent in all the six Mrg-Inds that require common ergonomics intervention at reducing health and safety risks of workers in food, textile, chemical, leather and shoe, furniture and wood, and metal Mrg-Inds.

Keywords: *Customized; Safety; Decision tree*

Introduction

Manufacturing is defined as the process of physically transforming goods which involves activities such as molding, cutting, and assembly. A manufacturing company is considered as a complex human-machine-environment-organization system. A manufacturing company contains a large number of systems which interact to transform raw materials into finished products (Livesey, 2006). Each country's economy depends on its manufacturing activities which serve as the hub of a vibrant national economy (Baldassarre, 2017). The growth rate of manufacturing industries (Mrg-Inds) in a country truly reflects its economic potential (Haraguchi et al., 2016). The manufacturing sector has many different types some of which include; food industry, textile, chemical, leather and footwear production, furniture and wood products, metal (Chete et al., 2016).

Evolution of Mrg-Inds skyrocketed risks and health challenges among its workforce. Different industries face different challenges. The risks and health challenges vary

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depending on the type of equipment adopted and raw materials used. Workers in Mrg-Inds spend most of their working hours at the workplace, but with little attention and resources provided by most employers to protect the health and safety of the workers, hazards and risks in Mrg-Inds are on the increase (Sengupta, 2007). Hazard can be described as the potential for harm. It is associated with a condition or activity that, if left uncontrolled, can result in an injury (Lu & Yang, 2011). Health and Safety Executive (2013) described hazard as any source of potential damage, harm, or adverse health effects on someone under certain conditions at work. Different hazards in many industries include but are not limited to; dust, temperature, biological agents, chemical agents, hand tools/ machinery, hazardous substances, slips, trips and falls, chemical agents, exposure to fibres, exposure to physical agents, flammable gases/liquids, and musculo-skeletal disorders.

Hazards in Mrg-Inds is a global challenge (Sengupta, 2007). In Indonesia for instance, a report in 2014 showed that there were 921,500 workers in the Mrg-Inds. This equated to 7.9% of the total Australian labour force. The industry had the highest average incidence and frequency rate of serious workers' compensation claims for the five-year period compared to other industries (Safe Work Australia, 2015). In the U.S., common non-fatal injuries include contact with objects, slips/trips/falls, and overexertion and bodily reaction were reported in Mrg-Inds (Bureau of Labor Statistics, 2015, 2017). Around 35.6 million of European Union workers were employed in the Mrg-Inds and in 2004, the incidence rate of serious and fatal accidents was about 4 million (European Agency for Safety and Health at Work (2009). The level of the reported occupational hazards in Mrg-Inds in Africa is low compared with the rest of the world (Aliyu & Saidu, 2011). In Egypt, a high rate of injuries resulting in fatality rate of 52.1% was reported. The Mrg-Inds in Nigeria is reportedly growing at a faster pace but actually contributed less to Nigeria's economy (Nasir, 2011). Nigeria did not report fatalities or accidents in Mrg-Inds to International Labour Organization for many years. However, the little information available about health and safety level in the sector indicated that workers in the manufacturing sector are exposed daily to a diversity of occupational health hazards (Omokhodion 2009; ILO, 2011)

Hazards exist everywhere and it is important to identify them to grow a safer environment. Safe workplaces are profitable, whether measured in a company's bottom line, its market share, its broader consumer reputation, or its ability to attract and retain workers (University of Newcastle, 2014). Hazards identification is one of the key elements of work-safe plan. There are many techniques available for hazards recognition. The use of artificial intelligence (AI) is reported as reliable among other methods (Barrett & Baum, 2017). AI is capable of emphasizing on the creation of machines that are intelligent and work like humans. Artificial intelligence machines are designed to undergo activities such as learning and problem solving. Different types of AI methods are available for machine learning. These include: fuzzy logic system, artificial neural networks, genetic algorithms, hybrid system, and decision tree, among others.

Decision Tree is among the principal machine learning techniques because of its rapid learning tasks and persistent prediction outcomes (Leong, 2014). A machine learning decision tree (Mld-tree) is a pictorial description of a well-defined decision problem. Decision nodes are often represented by squares showing decisions that can be made. Lines emanating from a square show all distinct options available at a node. Chance nodes are represented by circles showing chance outcomes. It is a step in the process which involves uncertainties and possible outcomes of probabilistic events. Terminal nodes are represented by triangles or by lines having no further decision nodes or chance nodes. Terminal nodes depict the final outcomes of the decision making process.

In using a machine learning decision-tree, it is first necessary to select an attribute to place at the root node, and make one branch for each possible value. Then the process can be repeated recursively for each branch, using only those instances that actually reach the branch. If at any time all instances at a node have the same classification, that part of the tree has to stop developing (Witten et al., 2011). According to Vandamme (2007), the way of finding the attribute that produces the best split in the data is one of the main differences between the various decision-tree-building algorithms. There are several measures of splitting criteria. Each decision tree algorithm use its own measure to select among the attributes at each step while growing the tree. There are various decision trees algorithms available; ID3 (Iterative Dichotomiser 3), C4.5, CART (Classification and Regression Tree), MARS, and CHAID (CHi- squared Automatic Interaction Detector).

CHAID, or CHi-squared Automatic Interaction Detector, is an algorithm that categorizes every variable to either ordinal or nominal variables. At each node it tries to find the best explanatory variable and the best merger of categories. It makes the distributions of cases across the response categories as different as possible in the ‘offspring” nodes (Kass, 1980). One of the many advantages derived using CHAID is that its output is highly visual and easy to interpret with multiple trees [You et al., 2015]. In CHAID analysis, the categorical data are divided into subgroups and their effects on the dependent variable are tested. The CHAID algorithm was first defined by Kass (1980) for dependent variables at the level of categorization. CHAID can be applied to continuous or discrete dependent and independent variables.

An Mld-tree is a powerful method for classification, prediction, and for facilitating decision making in sequential decision problems. The Mld-tree classifier has been widely used in a range of studies (Renuka et al., 2014) for risk assessment. The technique is simple and a powerful method of representing knowledge (Milovic & Milovic, 2012). It is envisaged that proper identification of prevalent hazards associated with activities/tasks in all Mrg-Inds will help to refocus administrators of the industries to the basic risk control decisions expected of them, ensuring the improved safety and health of their workers. This is the perception of the researchers in this study that aim at assessing the common hazards from all the personalized hazards and risks existing in food, textile, chemical, leather and shoe, furniture and wood, and metal Mrg-Inds. The objective is to integrate customized hazards risks using a Mld-tree approach so as to identify the area(s) requiring similar control and/or ergonomic interventions.

Materials and Methods

Study Design, Area and Subjects

In this study, a cross-sectional design was adopted. Data were collected from subset of the total Mrg-Inds populations. Six Mrg-Inds were involved in this study. These included food, textile, furniture and wood, chemical, leather, and metal.

The study was carried out in Lagos and Ibadan all within southwest Nigeria because of the concentration of Mrg-Inds in these locations. Lagos is the most urbanized city in Nigeria and has the highest number of different Mrg-Inds. Lagos has a population of about 10 million people. Ibadan is the third largest city in Nigeria by population and located approximately on longitude 3°55’00” east of the Greenwich Meridian and latitude 7°23’47” north of the Equator. The subjects involved in this study were randomly selected among those who have spent not less than 5 years in each of the industries. The subjects were 300 in total comprised of at least fifty participants from each of the industries.

Data Collection Procedures

A structured questionnaire was designed with the objective of determining the major hazards prevalent in all the industries included in the study. Respondents were requested to provide their opinions on each of the identified hazards based on its capability of causing injuries among workers on a five scale point (1 represented, 'low risk' and 5 represent 'very high risk') (independent variables). Participants were also asked to rate their subjective opinions about the level of hazards and risks in the workplace (dependent variables). The interview was conducted in the English language. On the average, each interview took about 45minutes.

To minimize risk of harm to all participants, the research received ethical approval before the commencement of the study. All subjects were fully informed of the reason for the study so that they can decide whether to participate or not. They were all assured that only the researcher will be aware of who has contributed. Consents were taken in written form from the managements of each industry involved, and in oral form from all other participants, after they were informed that their participation in the study was voluntary.

To avoid bias of data collection, indirect questions were included in the questionnaire. The interview also consisted of open-ended questions that allowed participants to express their opinions on additional information not provided in the structured questionnaire. Before final submission, participants were allowed to review their answers to ensure that they reflected on their views.

Development of Machine Learning Decision Tree and the Algorithm

Data Processing Paradigm. As shown in Fig. 1, the details of the dependent and independent variables formed the database which were subjected to CHAID algorithm in the Statistical Package for the Social Sciences (SPSS) software where the decision tree model was implemented.

CHAID Algorithms. CHAID is a type of decision trees derived using recursive partitioning data algorithms that categorized each incoming case into one of the class labels for the outcome. The CHAID algorithm as originally proposed by Kass (1980) allows multiple splits of a node. CHAID algorithms consist of three steps (merging, splitting and stopping) with which a tree is grown on each node from the root node.

If:

Y is the target variable and categorical with J classes, its class takes values in C = 1, ..., J. mX, m = 1, ..., M

Xm, m =1,. . . ,M the set of all predictor variables.

h= $\{xn, yn\}_{(n=1)}^{N}$ - the whole learning sample

Wn - the case weight associated with case n

fn - the frequency weight associated with case n.

For each predictor variable X , each final category of X will result in one child node if X is used to split the node. The merging step also calculates the adjusted p-value that is to be used in the splitting step.

$$F = \frac{\sum_{i=1}^{1} \sum_{n \epsilon D} w_n f_n I(x_n = i)(\bar{y}_i - \bar{y})^2 (I-1)}{\sum_{i=1}^{1} \sum_{n \epsilon D} w_n f_n I(x_n = i)(\bar{y}_i - \bar{y})^2 (N_f - I)} \quad (1)$$

$$p = Pr(F(I-1\, N_f - I) > F) \quad (2)$$

If X has 1 category only, it stops and sets the adjusted p-value as 1, If X has 2 categories, it moves to the last step. Else, an allowable pair of categories of X is located that is least significantly different. For the pair having the largest p-value, the p-value is checked if it is larger than a user-specified alpha-level (α) merge. If it does, this pair is merged into a

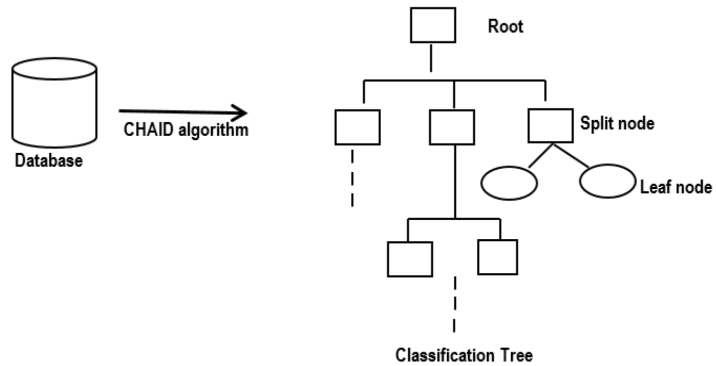

Figure 1. *Data processing paradigm of the tree model*

single compound category. Then a new set of categories of X is formed.

The adjusted p-value is computed for the merged categories by applying Bonferroni adjustments. The Bonferroni multiplier 'B' is the number of possible ways that 'I' categories can be merged into 'r' categories. For r= I, B =1. For 2$\leq$r $<$ I, using (3)

$$B = \sum_{v=0}^{r-1} (-1)^v \frac{(r-v)^I}{v!(r-v)!} \quad Nominal\ predictor \tag{3}$$

The splitting step selects which predictor to be used to best split the node. This is done by comparing the adjusted p-value associated with each predictor. The predictor that has the smallest adjusted p-value is selected.

The stopping step checks if the tree growing process should be stopped according to stopping rules (Bigss et al., 1991; ftp.software.ibm.com)

The Training and the Testing Phases. There are two phases involved in this study, the training and the testing. The training phase created the decision tree from the training data while the testing phase generated the tagged output based on the developed decision tree. All the observed data of the training sample were first randomly divided into Z disjunctive partitions of approximately the same size. The evaluation process is conducted through z iterations. In each iteration, a single subset is selected for testing while the union of other subsets (z-1) is used for model training. Training and testing were carried out at the same number of times. It started with the original set of attributes as the root node. Each iteration was done through every unused attribute of the remaining set, and calculated the information gain of that attribute. The attribute with the smallest entropy value was selected. The set of remaining attributes was split by the selected attribute to produce subsets of the data. The algorithm continues to recourse on each subset, considering only attributes never selected before.

At the testing phase, the trained decision tree was used to classify the new unseen test cases by working down the decision tree using the values of this test case to arrive at a terminal node that suggested the class of the test. This approach was selected because of good accuracy result with the use of discrete splitting and randomness. At the end of the procedure, overall accuracy was calculated as the arithmetic mean of z individual accuracies. Several iterations were preferred so as to achieve a more robust assessment of classification model accuracy.

To reduce over fitting in training sample, tree pruning methods which eliminate the statistically insignificant branches and redundant information was conducted

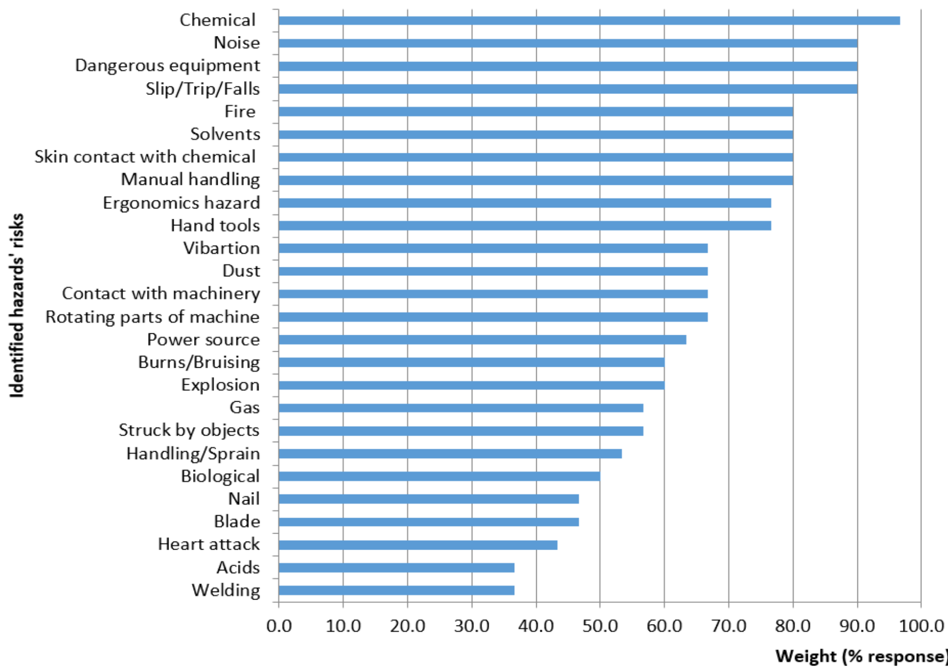

Figure 2. *Measured hazards risks in six manufacturing industries*

(Vercellis, 2009; Gorunescu, 2011; Milanović & Stamenkovic, 2016).

Results and Discussion

Hazards Risk Assessment

Figure 2 shows the hazards and risk attributes identified by assessors and those reported by the subjects in all the six industries. The risk attributes were grouped into 26. Out of these, explosion, burns/bruising, power source, rotating parts of machine, contact with machinery, dust, vibration, hand tools, ergonomics hazard, manual handling, skin contact with chemical, solvents, fire, slips/trips/falls, dangerous equipment, noise and chemical hazards were rated 60% prevalence and above.

However 'chemical' hazards had a weight of 96.8% and was rated the major contributor to hazards among the industries. This was followed closely by 'slips/trips/falls' (90%) and 'equipment' (90%). From the six industries (Table 1), the influence of 'chemical' hazards was noted common. All the industries were allocated 5 marks indicating a 'very high risk' except in 'furniture and wood industry' which was allocated with 4 marks (high risk). Hence chemical hazards is among the main hazard risks to control across all the industries. 'Slips/trips/falls' was also rated 'very high' across the industries. Except in the textile industry where 2 marks, representing 'low risk', was allocated to slips/trips/falls. Slips/trips/falls in every other industry was a 'very high' risk. This revealed that workers are always working at a particular height above their normal hand reach.

In terms of hazard risks across all the industries as shown in Fig. 3, all the studied Mrg-Inds were rated above 50%. There was no industry considered completely free from hazard risks. The 'furniture and wood' industry was however rated the highest in terms of concentrations of different risks of various hazards (76.9%). This was followed by the 'chemical' industry (70.8%), the 'metal fabrication' industry (68.9%), the 'leather and shoes making' industry (65.4%). The 'food industry' was the least (55.4%) among the group.

Table 1. Hazard risk assessment and prevalence in six different manufacturing industries

No	Hazards	Food	Textile	Chemicals	Leather	Furniture and wood	Metal
1	Noise	5	5	3	4	5	5
2	Ergonomics hazard	5	5	3	3	4	3
3	Slip/Trip/Falls	5	2	5	5	5	5
4	Chemical	5	5	5	5	4	5
5	Dangerous equipment	5	5	5	2	5	5
6	Biological	5	2	4	1	2	1
7	Vibration	2	5	5	3	3	2
8	Fire	3	5	5	1	5	5
9	Explosion	2	5	4	1	3	3
10	Dust	1	5	2	5	5	2
11	Acids	2	1	5	1	1	1
12	Solvents	3	3	5	5	4	4
13	Gas	2	2	5	1	2	5
14	Burns/Bruising	1	2	5	3	4	3
15	Skin contact with chemical	3	4	5	3	5	4
16	Heart attack	2	2	5	1	1	2
17	Handling/Sprain	1	1	1	5	4	4
18	Contact with machinery	3	3	3	5	4	2
19	Manual handling	3	3	3	5	5	5
20	Struck by objects	2	1	2	5	3	4
21	Hand tools	2	3	3	5	5	5
22	Blade	1	1	1	4	5	2
23	Rotating parts of machine	4	3	3	3	5	2
24	Power source	3	2	3	3	5	3
25	Nail	1	1	1	4	5	2
26	Welding	1	1	1	2	1	5

1= Very low risk, 5 = Very high risk

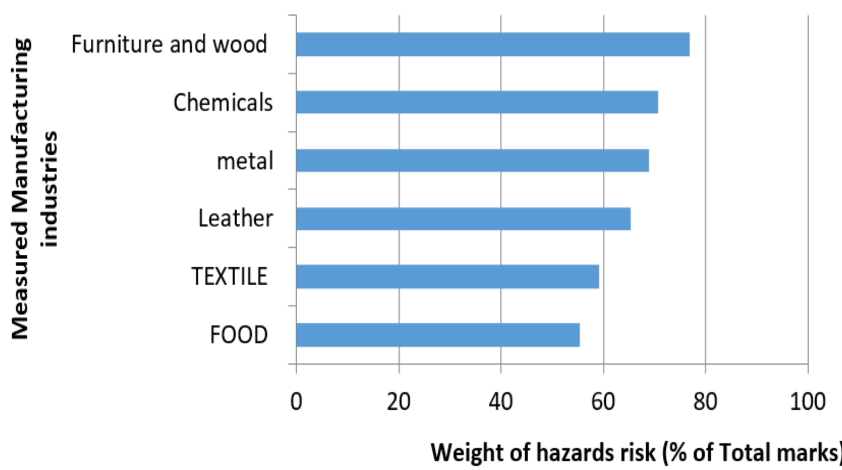

Figure 3. *Level of hazards risks prevalence base on types of manufacturing industry*

Furniture and wood making industry may have emerged the most dangerous in terms of hazard risks among all others due to use of chemicals such as different types of spray paint and dangerous machinery like band saw, bench grinder, etc. involved in the industry. Most of the equipment are sharp and rotatory. All the 26 hazards risks identified in this study except acids, biological, gas, heart attack, and welding were rated 'very high' in the 'furniture and wood making' industry.

Next to 'Furniture and wood' is the 'Chemical' industry. Hazards risks related to handling/sprain, blade, hand tools, nails and welding hazards were considered as 'low risk' in the industry. In the chemical industry, workers may hardly suffer from sprain injury due to handling of hand tools unlike other industries. Blade risks are not also common because there are minimal cutting operations in the industry. Welding operations are also restricted and most workers are not exposed to hazards related to welding operation. However other hazards are noted very high in the industry.

Food industry has the least risks of hazards among others. Unlike in other industries, hazards related to vibration, explosion, dust, acids, burns/bruising, heart attack, handling/sprain, struck by objects, hand tools, nails and welding were minimal and rated 'very low'.

Machine Learning Decision Tree Outcome

The Mld-tree for recognizing the fundamental hazards among all the industries is as shown in Fig. 4. The decision tree is displayed top down with the root node starting at the top. The model contained categorical dependent variables '1 = Very low risk', '5 = Very high risk'. Node definitions display the value(s) of the independent variable used at each node split. The tree started from the root node, the 'Fundamental Hazards', and was later splatted into a chance node.

The tree model shows that, 'Hazards related with equipment' and 'Ergonomics hazards' being the first chance node were common to all the industries. Hazards connected to equipment use in all the industries were recognized as required attention across all the industries. Hazards can result from equipment when left unguarded, when operators have no adequate knowledge of operation, when it is faulty etc. Unguarded machines can cause cuts, bruise, wounds, and lacerations among others.

Ergonomics hazards include repetitive work, awkward postures at work, and work stress, among others. These factors affect the safety and health of workers across industries. When efforts are not in place to reduce ergonomic hazards, workers are exposed to dangers related to musculoskeletal disorders. Enhanced ergonomic training is a measure that can help at reducing the effects of ergonomics hazards across the industries (Adeyemi et al., 2013). When workers are trained, they will know how best to handle the work, workstation, and their environment in general.

The chance node in the Mld-tree recognized 'Noise' when 'Hazards related with equipment' was further splatted into end node. Effects of 'noise' are noted common across all the industries and need attention. Noise can reduce the hearing ability of workers and may lead to permanent deafness. Engineering control is one key step that each industry can adopt to reduce the negative impact of noise. Equipment should be properly designed and installed to reduce noise level. Sound proofing of most equipment can also help.

The tree model is simple. It has 7 nodes, 5 terminal nodes and a depth of 2. This is considered to be good for a reliable model that can function in practical procedures where few independent (predictor) variables may be desired for easy descriptions

Evaluation of Model Quality

The risk and the classification of the model. Marks '3', '4' and '5' (Medium, high and very high respectively) were preferred in the development of the model. The model classified the risk in order of their importance and their effectiveness in causing hazards common to all the industries. Table 2 and 3 present the basic information about the performance of the developed CHAID model in terms of its accuracy and predictive potentials. Table 2 presents prediction risk as a percentage of inaccurately classified observations. To be precise, result of this study suggests that if the characteristics of an industry in terms of all the independent variables (hazards) are known, the risk that the industry will be inaccurately classified in terms of relevant hazards is 2.0%, while that

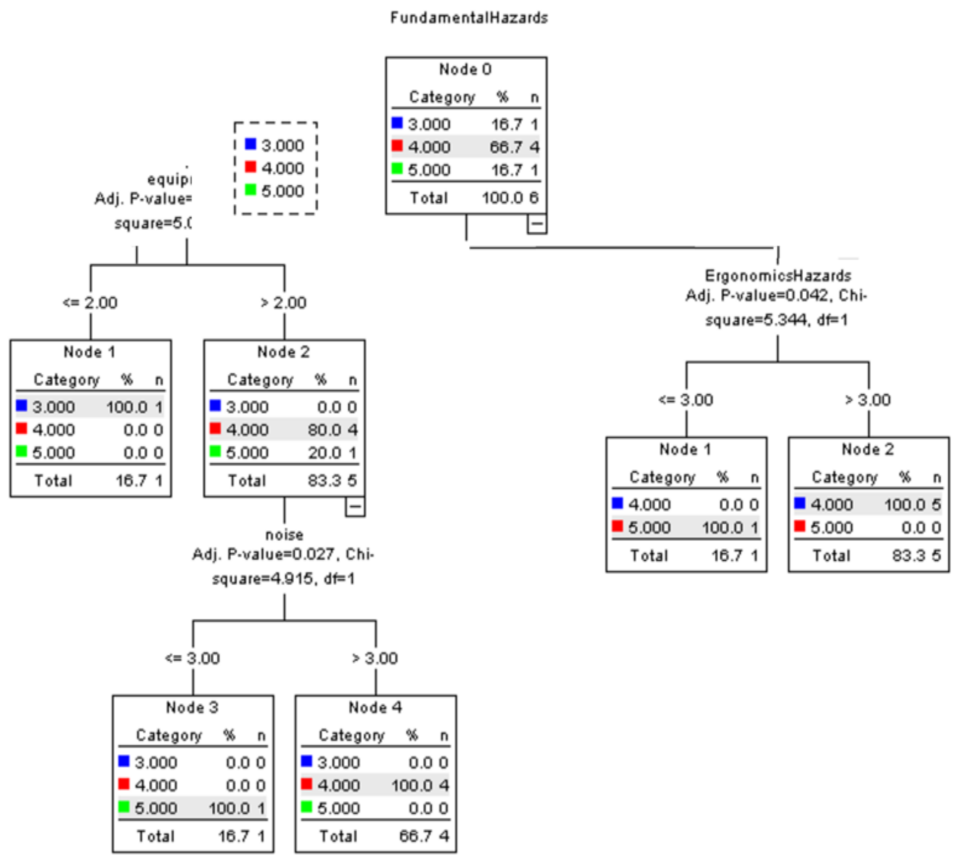

Figure 4. *Machine learning decision tree integrating the fundamental hazard risks among five manufacturing industries*

Table 2. Risk table

Re-substitution	Cross-validation
0.02	0.093

risk, when a test sample is used in model cross-validation is 9.3%.

Table 3 presents the classification matrix containing the actual (observed) and predicted classifications. It can therefore be stated that overall accuracy of the model is 99.5%. In other words, the model has accurately classified almost all of the hazards. However the percentages structure of modeled (predicted) values according to the categories of the dependent variables 'high risk' and 'very high risk' were 83.1% and 16.4% respectively.

Application of the machine learning decision tree. The Mld-tree decision tree

Table 3. The model classification table

Hazards severity	Predicted		
	4	5	Percent Correct
4	5	0	99%
5	0	1	98.3%
Overall Percentage	83.1%	16.4%	99.5%

in Fig. 3 can find applications in any of the industries studied. The use of the devise can also be extended to many others by incorporating their customized hazards. The importance of the device is to help in recognizing the most important areas where managers of all the studied industries can concentrate efforts to reduce the impact of the risks on their workers. The attributes recognized by the decision tree machine learning tool is considered as the integrated customized hazards across the industries and the common treat to workers across industries. If adequate attentions is given to reduce hazards in these areas, level of safety of workers will be enhanced across the industries.

The model however is specifically developed for the food, textile, chemical, leather and shoe, furniture and wood, and metal Mrg-Inds and may not be used for other industries not captured in the research.

Conclusion

This study aimed at reducing health and safety risks in manufacturing industries by assessing the possibility of integrating the customized hazard risks in six Mrg-Inds. The industries involved in this study include food, textile, chemical, leather and shoe, furniture and wood, and metal.

Twenty six potential hazards were initially recognized. 'Chemical' hazards was rated the major contributor of hazards across all the industries. This was followed closely by 'slips/trips/falls ' and 'machinery'. In terms of hazard risks, all the studied industries were hazard prone, rated above 50%. 'Furniture and wood' industry was however rated the highest in terms of risk of various hazards. This was followed by 'chemical' industry, 'metal fabrication' industry, 'leather' and 'shoes making' industry while ;food' industry had the least hazards the group.

The machine learning decision tree developed for recognizing the fundamental hazards across all industries spotted hazards related to 'equipment' and 'ergonomics' hazards' as the first chance node and the most common across industries. The chance node was 'noise' as the 'hazards related with equipment' was further splatted into end nodes. The decision tree can find applications in any of the industries studied. The attributes recognized by the machine learning decision tree tool were considered customized hazard risks across the six industries that required common ergonomics intervention.

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