The Use of Machine Learning and Big Five Personality Taxonomy to Predict Construction Workers’ Safety Behaviour

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Abstract: Research has found that many occupational accidents are foreseeable, being the result of people’s unsafe behaviour from a retrospective point of view. The prediction of workers’ safety behaviour will enable the prior insights into each worker’s behavioural tendency and will be useful in the design of management practices prior to the occurrence of accidents and contribute to the reduction of injury rates. In recent years, researchers have found that people do have stable predispositions to engage in certain safety behavioural patterns which vary among individuals as a function of personality features.

In this study, an innovative forecasting model, which employs machine learning algorithms, is developed to estimate construction workers’ behavioural tendency based on the Big Five personality taxonomy. The data-driven nature of machine learning technique enabled a reliable estimate of the personality-safety behaviour relationship, which allowed this study to provide novel insight that nonlinearity may exist in the relationship between construction workers’ personality traits and safety behaviour. The developed model is found to be sufficient to have satisfactory accuracy in explaining and predicting workers’ safety behaviour. This finding provides the empirical evidence to support the usefulness of personality traits as effective predictors of people’s safety behaviour at work. In addition, this study could have practical implications. The machine learning model developed can help identify vulnerable workers who are more prone to undertake unsafe behaviours, which is proven to have good prediction accuracy and is thereby potentially useful for decision making and safety management on construction sites.

Keywords: Construction Sector, Machine Learning, Personality Taxonomy, Safety Behaviour.

1 Introduction

The construction sector plays a significant role in the economy growth [37]. This sector contributed 13% to global Gross Domestic Product (GDP) in 2018 and activities in this sector created infrastructure that can facilitate other sectors to operate efficiently [69]. However, safety issues follow upon such achievements. In recent years, the construction sector has reached a record of high accident rates [9]. In New Zealand, for instance, this sector had the highest accident rate (12.3 per 100000 workers) in 2017,
causing losses of about $80 million [3]. In the US, the construction sector caused 1171 non-fatal and fatal injury claims in 2018, which accounted for 18% of all industrial accidents [11]. In the UK, construction was responsible for the largest portion of all occupational injuries in 2018 with an incidence rate of 21% [43]. In Japan, more than one-third of all industrial accidents occurred in the construction sector in 2018, which resulted in 7,500 working days being lost [70]. Although the application of safety management practices seems to have made an impact on the reduction of injury and fatality rates, occupational accidents remain a pervasive issue in the construction sector [28].

Investigating the root causes of occupational accidents has been a pivotal focus of contemporary safety research [71]. Research has found that many occupational accidents are foreseeable, being the result of people’s unsafe behaviour from a retrospective point of view [2,24,27,28,113]. Engaging in such unsafe behaviours includes, for example, ignoring safety rules, failing to follow safety procedures, and not using safety equipment [62]. Accordingly, researchers started to investigate individual differences in order to explain and predict workers’ unsafe behaviours [72]. Gaining priori insights into workers’ behaviours can be useful in the context of safety management [13]. As Patel and Jha [72] have pointed out, safety management practices are proactive interventions and incentives established to prevent the occurrence of accidents. The behaviour prediction in advance can help identify vulnerable workers who are more prone to undertake unsafe behaviours, which will be useful in the design of management practices prior to the occurrence of accidents and contribute to the reduction of injury rates [13]. In addition, the workers’ behaviour prediction can improve their self-awareness and knowledge on their own behavioural responses and associated risks, which will be helpful to motivate workers to work safely and take their own safety more seriously [72].

In recent years, researchers have found that people do have stable predispositions to engage in certain safety behavioural patterns which vary among individuals as a function of personality features [14,40]. For example, Jirjahn and Mohrenweiser [47] noted that individuals with a high score in sensation seeking (a personality trait at facet level) had a high probability of conducting risk-taking activities at work. Hidayat, et al. [42] found that workers high in neuroticism (a personality trait at broad level) were prone to exhibiting negative emotions and distracted thinking, which could predispose themselves to behave unsafely. Beus, et al. [10] conducted a meta-analysis and ascertained that people’s personality features were intrinsically linked to their safety behaviour in occupational settings. Existing literature has also provided empirical evidence to support the usefulness of personality traits as effective
predictors in explaining people’s safety behaviour at work [10,26,90].

The latest literature reveals that traditional safety behaviour prediction based on personality traits for construction workers relies on the linear regression (LR) method [5,29,40,46,90]. However, a major drawback of LR is that it is a linear rule-based method which maps the relationship among variables of interest by imposing a linearity assumption on the data [51]. This linearity assumption does not hold good for nonlinear settings, which transforms the nonlinear nature into a linear character and may lead to inaccurate prediction results [86]. Although LR models have been developed to utilise personality traits to predict construction workers’ safety behaviour [46,90], it remains unclear whether LR can capture the actual relationship between workers’ safety behaviour and personality traits [109]. As pointed out by Reimer, et al. [82], an assumed mathematical linear relationship does not necessarily imply that the actual relationship is linear. Beus, et al. [10] also suggest that in addition to the relatively simple mathematical form of linear models, the predictive relationship between personality and people’s work behaviour may be more complex (e.g., nonlinear and vague). This raises doubts about the validity of the LR models developed in previous studies.

In recent years, machine learning (ML) has gained significant popularity in the field of statistical prediction [35]. In contrast to the rule-driven nature of LR, ML is a data-driven method that allows identifying natural patterns between variables of interest without assuming any preconception in terms of the mathematical structure of the data and uses algorithms to build models based on data in order to make inferences about likely future outcomes [95]. ML techniques such as neural network and decision tree have been proven to achieve high accuracy levels in the determination of complex relationships in various fields such as medical diagnosis, stock market prediction, speech recognition, face recognition, and behaviour prediction [66]. It has also been pointed out that ML can model both nonlinear and linear relationships and provide better prediction accuracy than LR [20]. This can overcome the linearity limitation of the LR models developed in previous studies as mentioned above. In order to contribute to the growing research literature in this field, this study aims to apply the ML method to develop a more reliable estimate of the relationship between construction workers’ personality traits and safety behaviour for the prediction of workers’ safety behaviour.

In addition, it has been found that the existing literature has only theoretically speculated that ML models might yield better prediction accuracy than the traditional LR method given the advantages of ML (e.g., free from the linearity limitation) [48,72], and have provided no solid empirical data to support
this theoretical speculation. Without such evidence, the utility of ML over LR for the prediction of construction workers’ safety behaviour remains undetermined. As a validation, the authors will also develop a LR model and compare the prediction accuracy against the ML model.

This paper is organised as follows. Section 2 specifies the stages involved in this study as the research method. The development of the ML and LR models is presented in Section 3. Next, the results, which involve the evaluation and comparison of the prediction accuracy of the ML and LR models, are discussed in Section 4. Finally, Section 5 summarises the results, interprets the practical implications, lists the limitations, and recommends future research directions.

2 Research Method

In order to develop a ML model to predict construction workers’ safety behaviour based on personality traits and contrast its prediction accuracy against the LR method, the following research steps suggested by Kannan and Vasanthi [52] were conducted in this study: preparing the data, initialising the data structure, selecting the ML technique, developing the ML and LR models, and comparing the prediction accuracy of the ML and LR models. The workflow is discussed in greater detail in the following subsections.

2.1 Preparing the Data

Collecting relevant data for model development is a critical first step in this research. As mentioned in Section 1, this research aims to predict construction workers’ safety behaviour based on personality traits. A survey was thus conducted with the objective to gather data concerning personality traits and safety behaviour of construction workers.

2.1.1 Survey Instruments

The survey instruments were composed of three parts.

2.1.1.1 Demographic Information

The first part asked for demographic information from respondents, namely, age, years of work experience, and type of trade (e.g., Carpenter and Joiner, Mason, Electrician).

2.1.1.2 Personality Measurement

In the second part, the respondents were asked to self-rate their personality traits. As previous studies have pointed out [17,57], the Big Five Inventory (BFI) by John, et al. [49], the NEO Five-Factor Inventory (NEO-FFI) by Costa and McCrae [15], and the Revised NEO Personality Inventory (NEO-PI-R) by Costa and McCrae [16] are the three well accepted and widely used instruments for personality
measurement. The psychometric properties (i.e. reliability and validity) of these instruments have been assessed extensively by numerous researchers and have been proven to be highly reliable and valid [e.g., 39, 53, 57]. From a practical point of view, the BFI has been recommended to be more useful than NEO-FFI and NEO-PI-R for being brief [83]. Huang [44] has estimated that the BFI, NEO-FFI and NEO-PI-R are composed of 44, 60 and 240 items respectively and take approximately 5, 10 and 45 minutes to complete respectively. Lengthy instruments can cause respondents to generate negative attitudes towards the survey (e.g., becoming fatigued, refusing to participate, and responding in a careless manner), which may influence the validity of the data gathered [7]. Considering the above discussion, the BFI was selected as the instrument for personality measurement in this study, which is a 44-item psychological measure of five personality traits: extraversion, agreeableness, conscientiousness, neuroticism, and openness [49] (Appendix A).

In addition, it has been pointed out that the BFI as well as NEO-FFI and NEO-PI-R was developed purposely for the general measure of personality [7], and general personality items can cause individuals to perceive the context of the items differently [64]. For example, in response to the item “Q18: I see myself as someone who tends to be disorganised” in the BFI (Appendix A), people’s perceptions of the context can differ from one another (e.g., workplace or non-workplace) [7]. This may influence their responses to the item as individuals can act differently in different contexts, for example, highly organised in the workplace (e.g., maintaining a tidy workspace) but disorganised at home (e.g., accumulating dirty laundry) [97]. It has been pointed out that the BFI items can usefully be adapted to derive contextualised measures [21]. To enhance the specificity of the BFI for personality measurement in the work context, Schmit, et al. [85] have developed the work-specific BFI by appending a reference to work (i.e. “at work”) to each item in the BFI. As also pointed out by Schmit, et al. [85], the openness sub-scale (see Appendix A) was not included in the work-specific BFI because they found that: 1. The appendage of “at work” could not meaningfully fit into many items in the openness sub-scale (as suggested by the safety experts participated in their study to evaluate the content validity of the work-specific BFI); and 2. No correlation could be identified between openness and people’s safety behaviour at work. This has also been further confirmed by a meta-analysis conducted in recent years [10] that no correlation could be found between openness and people’s safety behaviour in the workplace.

The psychometric properties (i.e. reliability and validity) of the work-specific BFI have been examined extensively by numerous researchers and have been proven to be highly reliable and valid.
Taking the above considerations into account, the work-specific BFI was used as the instrument for personality measurement in this research, which is a 34-item psychological measure of four personality traits: extraversion, agreeableness, conscientiousness, and neuroticism (Appendix B).

2.1.1.3 Behaviour Measurement

The third part of the survey asked respondents to self-report their safety behaviour. The Safety Behaviour Scale (SBS) by Hayes, et al. [41] (Appendix C) was used in this research due to the following advantages. First, as Panuwatwanich, et al. [71] have pointed out, a thorough prediction of workers’ safety behaviour should include two main components, namely, task performance and contextual performance. Task performance refers to compliance-related behaviour that individuals carry out to keep themselves safe such as not taking shortcuts, using safety equipment, and following safety procedures and rules. Contextual performance refers to voluntary safety activities such as reporting safety problems, keeping workplace clean, and caring for colleagues’ safety, which may not directly contribute to one’s own safety but help to develop an environment that supports safety. As it is apparent from Appendix C, the SBS contains a wide variety of behavioural topics to measure task performance and contextual performance such as taking shortcut, using safety equipment, following safety procedures and rules, reporting safety problems, keeping workplace clean, and caring for colleagues’ safety.

Second, to the best of our knowledge, the use of the SBS can provide a more adequate assessment of safety behaviour than some of the instruments used in previous studies in the field of construction management. For example, Patel and Jha [72] assessed construction workers’ safety behaviour by implementing a single item “I (self) follow all of the safety procedures for the jobs that I perform”. Guo, et al. [37] used four items to assess construction workers’ safety behaviour in terms of using safety equipment and other behavioural topics such as following safety procedures were not included in their survey instruments. Third, the SBS has additional advantages of being brief (11 items) and possessing very good reliability (0.85) given the threshold (above 0.70) [96], as reported in the original paper [41].

2.1.2. Survey and Participants

The survey was launched in April 2018. Ethical approval was granted by the University of Auckland Human Participants Ethics Committee. The respondents were informed that their participation in this study was entirely voluntary, and they were free to withdraw from participation at any time without any explanation. Two hundred and eighty workers finally responded to the survey. They are from six
construction companies in Auckland, New Zealand. Of the 280 responses, 12 were deemed unusable due to having unanswered items or containing long rows of the same answer and dropped from this study. The remaining 268 responses indicated an overall usable rate of 95%. Table 1 reports the distribution of demographic characteristics of the respondents. Note that the respondents were composed of individuals employed in different construction trades and almost half of them had worked at a minimum of five years on construction projects.

**Table 1. Demographic Characteristics**

| Features                  | Categories       | Respondents |       |
|---------------------------|------------------|-------------|-------|
|                           |                  | Frequency   | Percentile (%) |
| Age                       | 20-29            | 164         | 61.2  |
|                           | 30-39            | 75          | 28.0  |
|                           | 40-49            | 27          | 10.1  |
|                           | > 50             | 2           | .7    |
| Work Experience (Years)   | 0-5              | 139         | 51.9  |
|                           | 6-10             | 43          | 16.0  |
|                           | 11-15            | 32          | 11.9  |
|                           | 16-20            | 33          | 12.3  |
|                           | > 20             | 21          | 7.8   |
| Type of Trade             | Mason            | 44          | 16.4  |
|                           | Carpenter and Joiner | 20 | 7.5    |
|                           | Electrician      | 13          | 4.9   |
|                           | Foreman          | 11          | 4.1   |
|                           | Miscellaneous Labourer | 84 | 31.3   |
|                           | Plant Operator   | 25          | 9.3   |
|                           | Plumber          | 24          | 9.0   |
|                           | Welder           | 25          | 9.3   |
|                           | Project Manager  | 15          | 5.6   |
|                           | Painter          | 7           | 2.6   |

**2.2. Initialising the Data Structure**

Data structure represents the architecture of the dataset used for developing ML models [68]. A functional data structure consists of an input matrix ($I$) and an output matrix ($O$) [77]. Figure 1 shows the data structure initialised for the prediction model to be constructed in this study. As can be seen, the dataset presents a multiple-input–multiple-output structure. The input consists of a 268x4 matrix, which represents 268 samples of four personality traits (i.e. extraversion, agreeableness, conscientiousness, and neuroticism). The output is a 268x2 matrix, which characterises 268 samples of two safety behaviour indicators, namely, task performance and contextual performance.
2.3. Selecting the Machine Learning Technique

ML techniques can be grouped into two categories based on the learning mechanism: supervised and unsupervised learning [52]. Supervised learning uses a dataset of input and known responses to the input and builds a model to generate predictions for the responses to new input [82]. Unsupervised learning is used to find hidden groupings in data, which draws clustering inferences from datasets consisting of only input without responses [110]. According to the above classification, supervised learning is clearly the appropriate technique for our prediction task.

Neural network and decision tree represent the leading techniques for supervised learning [77]. A neural network is a mathematical model consisting of thousands of artificial "biological neurons" that imitates the way human brain functions such as the process of learning, information processing, generalisation, and adaptation [88]. A decision tree resembles the branching structure of tree, where each node indicates a decision criterion and each branch illustrates a possible outcome of a decision [73]. The authors found that decision tree demonstrates several shortcomings compared to neural network. First, it has been pointed out that decision tree is applicable for training simple nonlinear models whereas neural network can map much more complex logical rules and enable more accurate boundaries [12]. Second, decision tree is more prone to overfitting [82]. Overfitting denotes the phenomenon that the learning system overly adapts to the training dataset and even the noise in data,
which affects the prediction accuracy of the trained model for new input [31]. Neural network has been shown to have high affordability to noise in data and yield good performance on a wide variety of prediction problems such as medical diagnosis [60], financial forecasting [104], and behaviour prediction [67]. Third, decision tree is inherently unstable and more sensitive to small perturbations in the data compared to neural network as slight changes in the input can lead to completely different tree structures [34]. Fourth, another limitation of decision tree lies in its low tolerance to high-dimensional data (i.e. data with a large number of variables) [73]. Neural network has been found to allow efficient handling of high-dimensional data [45]. The shortcomings of decision tree provided strong reasons for favouring neural network, which is therefore utilised in this study to construct the prediction model.

The neural network technique contains three types of commonly used architectures, namely, feedforward neural network (FNN), recurrent neural network (RNN), and convolutional neural network (CNN) [78]. The FNN is primarily used to develop predictive models where the input and known responses to the input should be statistical data provided in tabular format [88]. The major advantage of RNN resides in its unique ability to handle data in text and speech formats and perform tasks such as speech recognition [35]. For CNN, its main domains of application are image data processing, image recognition and image clustering [112]. Note that our data are statistical and in tabular format. Thus, the FNN was assumed to be the most suitable architecture for the purpose of this research.

Training a neural network involves employing an algorithm to adjust the model weights to approximate the mapping between its input and output layers [111]. Previous studies have indicated that back-propagation (BP) is the standard algorithm used in training FNN [65,79,105]. The basic idea of the BP algorithm is to propagate the network error (i.e. sum squared error between the predicted and actual outputs) back from the output layer to the input layer and repeatedly adjust each weight in the network to minimise the error [79]. The BP algorithm presents several advantages. First, it has been proven to be efficient in forming arbitrary complex mappings [111]. Second, it is the easiest algorithm to implement with only few parameters to adjust such as number of hidden neurons and number of hidden layers [6]. Third, it has been proven to have good prediction accuracy and adequate reliability [99,110]. Fourth, it consumes less working memory and computation time than most existing learning algorithms [93]. Fifth, it is based on rigorous mathematical foundation (i.e. gradient descent) and has shown its usefulness in science, engineering, and mathematics fields [12].

Although the advantages of the BP algorithm are widely recognised, the authors note that it may
have potential limitations. The convergence speed of the BP algorithm is slow, which may cause the training to become entrapped in the error minimisation process and result in the overfitting problem [108]. Some studies have recommended that the BP algorithm can be used in combination with a powerful optimisation algorithm—Levenberg-Marquardt (LM)—to overcome the limitation of slow convergence [e.g., 72, 106, 108]. The LM has been proven to be a faster and more efficient learning algorithm and can be used to hasten the convergence of the BP algorithm to prevent the training from getting trapped in the error minimisation process and avoid overfitting [84].

As a result, the FNN with the LM-BP algorithm was selected as the ML technique to perform the prediction task in this study.

2.4. Developing the Machine Learning and Linear Regression Models

In this step, the ML and LR models are developed to estimate the relationship between construction workers’ personality traits and safety behaviour for the prediction of workers’ safety behaviour. Details are to be provided in Section 3.

2.5. Comparing the Prediction Accuracy of the Machine Learning and Linear Regression Models

In this step, the prediction accuracy of the developed ML and LR models is evaluated and compared. The results are to be presented in Section 4.

3 Developing the Machine Learning and Linear Regression Models

3.1. Developing the Machine Learning Model

As mentioned, the FNN with the LM-BP algorithm was selected as the ML technique to perform the prediction task in this study. A FNN consists of multiple conductive layers, where the input layer is connected to the output layer through a number of neurons in the hidden layer [93] (Figure 2). The neurons in the input, hidden and output layers are responsible, respectively, for receiving input signals, processing the received signals, and decoding the processed signals into the outputs [8]. The output of a FNN depends on the weights between neurons in different layers and the biases of neurons in the hidden and output layers [78] (Figure 2). Weight indicates the strength of a particular connection between two neurons [88]. For example, the weight index $W_{j,k}^H$ in Figure 2 refers to the strength of the connection between the $j^{th}$ input neuron and the $k^{th}$ hidden neuron. Bias can be considered as an additional input to each neuron, which is a constant and is used to adjust the input sum to each neuron to increase the computational capability of the FNN [33]. For example, the bias index $bias_k^H$ in Figure
2 refers to the bias of the \( k \)th hidden neuron. During a learning process applying the LM-BP algorithm, the FNN iteratively adjusts the weight and bias values to minimise the error between the predicted and actual outputs [79].

![Diagram of an FNN](image)

**Fig. 2. The Architecture of an Example FNN**

For development of a FNN, the steps involved include specifying the number of hidden layers, selecting the combination of activation functions, determining the number of neurons in the input, hidden, and output layers, determining the data split ratio, and training the FNN [8]. Each step is described in greater detail below.

### 3.1.1. The Number of Hidden Layers

In general, a FNN has only one input layer and one output layer, and there can be one or more hidden layers in between [33]. It has been pointed out by many researchers that a single hidden layer is sufficient for a FNN to approximate any complex nonlinear mappings with desired accuracy [e.g., 22,60,75]. According to above considerations, the three-layer FNN (i.e. one input layer, one hidden layer, and one output layer) was used in this study.

### 3.1.2. The Combination of Activation Functions

The next step is to select the combination of activation functions [84]. In a FNN, activation functions run on neurons in the hidden and output layers, transforming a neuron’s input signal into an output
signal [63]. The commonly used activation functions are \textit{tansig}, \textit{logsig} and \textit{purelin} [84]. The \textit{tansig} and \textit{logsig} are nonlinear functions and the \textit{purelin} is a linear function [76]. Shen, et al. [89] pointed out that nonlinear functions (\textit{tansig} and \textit{logsig}) are capable of more complex computational rules than the linear function (\textit{purelin}). The hidden layer of the FNN performs computations on the network inputs and transfers the computed results to the output layer, and nonlinear functions (\textit{tansig} and \textit{logsig}) are commonly used in the hidden layer to increase the computational capability of the FNN [38]. In particular, among the nonlinear functions, \textit{tansig} has been previously proven to have better performance than \textit{logsig} for achieving higher prediction accuracy with less working memory and training time required [e.g., 1,50]. Considering the above discussion, the nonlinear function \textit{tansig} was used in the hidden layer.

In addition, Zarei and Behyad [107] pointed out that the output layer of the FNN decodes the computed results obtained in the hidden layer to provide the final output, and the activation functions used in the output layer can determine the output range of the FNN. The output ranges are different among the activation functions, where the output of the linear function (\textit{purelin}) can take on any value along a continuum from negative infinity to positive infinity and the output of nonlinear functions (\textit{tansig} and \textit{logsig}) is limited to the ranges of -1 to 1 and 0 to 1 respectively [19]. In this study, participants were asked to self-report their safety behaviour using a five-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, 5 = strongly agree) (Appendix C). Their overall safety behaviour score as the output of the FNN is calculated by summing the scores on all items (Appendix C) and then averaging, and can thus take on any value in the range from 1 to 5. Considering the above discussion, the linear function \textit{purelin} was used in the output layer to widen the output range of the FNN.

3.1.3. The Number of Neurons in the Input, Hidden, and Output Layers

In addition to specifying the number of hidden layers and selecting the combination of activation functions, another important task is to determine the number of neurons in the input, hidden, and output layers [8]. In this paper, the network has four input neurons (one for each personality trait) and two output neurons (one for each safety behaviour indicator). In order to determine the number of hidden neurons, a method widely recommended and used in the literature was followed: \( m \leq n \leq 2m \), where \( n \) is the number of hidden neurons and \( m \) is the number of input neurons [e.g., 20,58,95]. As noted in Patel and Jha [72], the process of determining the number of hidden neurons is also the process of
identifying the network with the best performance. Therefore, several training trials were conducted in Matlab, varying the number of hidden neurons from four to eight \((m \leq n \leq 2m)\), to identify the best performing network by examining two statistical parameters (i.e. mean squared error (MSE) and coefficient of determination \((R^2)\)), as suggested by many researchers [e.g., 80,94].

MSE and \(R^2\) are the most common measures of network performance as they indicate the global goodness-of-fit [78]. The values of MSE and \(R^2\) are between zero and one: for MSE, a lower value indicates a better goodness-of-fit; for \(R^2\), a higher value indicates a better goodness-of-fit [78]. The datasets used in the training and testing procedures are described in Section 3.1.4.

3.1.4. Determining the Dataset Split Ratio

In order to enable the evaluation of network performance, the whole dataset is usually divided into three groups, the training dataset, the validating dataset, and the testing dataset [80]. The training dataset is used to adjust the network parameters (i.e. weights and biases) to best map the input-output relationships [55]. The validating dataset is used to guarantee that the network is not overfitted while training [61]. As noted in Ramkumar, et al. [80], it is possible for a network to overfit the training dataset when the MSE value for the validating dataset starts to increase, and the training will be stopped at this point to prevent the network from overfitting. Finally, the testing dataset is established to evaluate the performance of the network after its development [94].

The following criteria for determining the dataset split ratio have been recommend in the literature [61,81]: 1. The training dataset should be more than two-thirds of the whole dataset, and then the validation and testing datasets should be equally split among the rest; and 2. Each of the validation and testing datasets should be approximately one-fourth to one-eighth of the training dataset. Given the criteria, the commonly applied split ratios include 70:15:15 and 80:10:10 for training, validation and testing datasets [56,101]. Additionally, the 70:15:15 has been reported to be a more balanced split ratio than 80:10:10 as it includes as many data points for training as possible and also preserves sufficient data portions for validation and testing [81]. In this study, the 70:15:15 ratio was therefore selected. The whole dataset has a total of 268 valid samples, of which 188 (70%), 40 (15%), and 40 (15%) samples were randomly assigned for training, validating, and testing of the proposed network.

3.1.5. Training the Feedforward Neural Network

As mentioned in Section 3.1.3, the training of the proposed network was carried out repeatedly with different numbers of neurons in the hidden layer (from four to eight). To determine the best performing
network, two statistical parameters, MSE and $R^2$, were estimated and compared for the training and validating datasets. The results are presented in Table 2. The authors found that the hidden layer with eight neurons provided the best performance among all alternatives, showing the least MSE and highest $R^2$ values. As a result, the 4-8-2 (four input neurons-eight hidden neurons-two output neurons) was considered the best performing configuration and determined for the proposed network.

Table 2. Statistical Parameters of Neural Network Models

| Number of Hidden Neurons | Data Sets | MSE   | $R^2$  |
|--------------------------|-----------|-------|--------|
|                          | Training  | Validating |       |        |
| 4                        | 0.205     | 0.258  | 0.653  |
| 5                        | 0.235     | 0.194  | 0.774  |
| 6                        | 0.186     | 0.178  | 0.814  |
| 7                        | 0.179     | 0.188  | 0.819  |
| 8                        | 0.140     | 0.130  | 0.852  | 0.871  |

While training the network, its weights between neurons in different layers and biases of hidden as well as output neurons were adjusted by applying the LM-BP algorithm in Matlab to best map the input-output relationships [55]. The weights and biases of the best performing configuration (4-8-2) are provided in Table 3.

Table 3. Weights and Biases

| Input / Output Neurons ($I_i / O_i$) | Weights /Bias | Hidden Neurons ($H_k$) |
|-------------------------------------|---------------|------------------------|
|                                     | $w_{1,k}^{H}$ | $H_1$, $H_2$, $H_3$, $H_4$, $H_5$, $H_6$, $H_7$, $H_8$ |
| $I_1$                               | 0.617         | 0.100 -0.459 0.065 3.925 1.434 3.006 -2.514 |
| $I_2$                               | -4.368        | 1.439 -2.976 0.342 3.888 -0.671 1.456 1.332 |
| $I_3$                               | 1.888         | -1.036 2.561 -0.369 -0.734 -8.384 -1.224 1.200 |
| $I_4$                               | 2.222         | -0.722 1.070 -0.186 -1.412 -0.783 3.461 0.957 |
|                                     | $w_{4,k}^{H}$ | bias $^{H_k}$ |
|                                     | -1.303        | -1.255 2.168 -0.136 0.190 3.776 3.004 -5.919 |
| $O_1$                               | $w_{1,1}^{H_O}$ | -0.469 2.493 0.325 -5.334 0.200 1.535 0.038 1.301 |
| $O_2$                               | $w_{2,2}^{H_O}$ | -0.717 -0.363 -1.189 -4.906 0.284 4.369 -0.826 3.982 |
|                                     | $bias_i^{O}$  | 0.774 (for $O_1$) 0.513 (for $O_2$) |
Notes: $I_j = \text{the } j^{th} \text{ input neuron}; H_k = \text{the } k^{th} \text{ hidden neuron}; O_i = \text{the } i^{th} \text{ output neuron}; w_{j,k}^{IH} \text{ (i.e. } w_{1,k}^{IH}, w_{2,k}^{IH}, w_{3,k}^{IH}, w_{4,k}^{IH} \text{) = the weight between the } j^{th} \text{ input neuron and the } k^{th} \text{ hidden neuron; } w_{k,j}^{HO} \text{ (i.e. } w_{k,1}^{HO}, w_{k,2}^{HO} \text{) = the weight between the } k^{th} \text{ hidden neuron and the } i^{th} \text{ output neuron; } \text{bias}_{k}^{H} = \text{the bias of the } k^{th} \text{ hidden neuron; } \text{bias}_{i}^{O} = \text{the bias of the } i^{th} \text{ output neuron.}$

3.1.6. The Architecture of the Developed Feedforward Neural Network

Figure 3 provides an overview of the architecture of the developed network. The input $I$ is a 4x1 matrix, which represents a unit of four personality traits, namely, extraversion, agreeableness, conscientiousness, and neuroticism. The size of the first weight matrix $W_1$ is 8x4, which connects four input neurons to eight hidden neurons. The second weight matrix $W_2$ is a 2x8 matrix, which indicates the connections between eight hidden neurons and two output neurons. The bias matrices $b_1$ (8x1) and $b_2$ (2x1) in Figure 3 indicate the biases of eight hidden neurons and two output neurons. As shown in this Figure 3, the developed network has its hidden and output layers built on the nonlinear function tanh and linear function purelin respectively. The matrix $a_1$ is the output of the hidden layer, where the input matrix $I$ is first multiplied by the weights $W_1$ and then the multiplication outcome is added with the biases $b_1$ and forwarded to the tanh function. The matrix $a_2$ (2x1) is the output of the network, which represents a unit of two safety behaviour indicators, namely, task performance, and contextual performance. To obtain the matrix $a_2$, the matrix $a_1$ is multiplied by the weights $W_2$ and then the multiplication outcome is added with the biases $b_2$ and forwarded to the purelin function.

As a result, the output matrix $a_2$ can be calculated using the following formulas:

$$a_1 = \text{tanh}(W_1I + b_1)$$

$$a_2 = \text{purelin}(W_2a_1 + b_2)$$

Fig. 3. Architecture of the Developed Network
where \( I \) = input matrix; \( W_1 \) = weight matrix (including weights between input and hidden neurons); \( W_2 \) = weight matrix (including weights between hidden and output neurons); \( b_1 \) = bias matrix (including biases of hidden neurons); \( b_2 \) = bias matrix (including biases of output neurons); \( a_1 \) = output of the hidden layer; \( a_2 \) = output of the network; \( N_j \) = the total number of input neurons (\( N_j = 4 \)); the definitions and values of \( w_{j,k} \), \( w_{k,i} \) (e.g., \( W_{j,1}^{IH} \, \, \, W_{j,8}^{IH} \), \( W_{k,1}^{HO} \, \, \, W_{k,2}^{HO} \), \( b_{j,k}^{H} \), \( b_{k,i}^{O} \)) can be found in Table 3.

### 3.2. Developing the Linear Regression Model

LR is a statistical method used to model the relationship between an output variable and one or more input variables by fitting all data points to the linear form [51]:

\[
y = b_1 x_1 + b_2 x_2 + \cdots + b_n x_n + c,
\]

where \( y \) is the output variable, \( x_i \) is the \( i \)th input variable, \( b_i \) is the weight of the \( i \)th input variable, and \( c \) is a constant which is used to adjust the sum of weighted input variables to best approximate the output variable. Using the dataset which includes the 188 training samples and 40 validing samples as assigned in Section 3.1.4, the LR calculation was performed using the computer programme SPSS [86], and the following LR formulas were obtained for the prediction of construction workers’ safety behaviour:

\[
y_1 = -0.086x_1 + 0.554x_2 + 0.543x_3 - 0.166x_4 + 0.658 \tag{5}
\]

\[
y_2 = -0.132x_1 + 0.755x_2 + 0.343x_3 - 0.170x_4 + 1.011 \tag{6}
\]
where $y_1 =$ task performance; $y_2 =$ contextual performance; $x_1 =$ Extraversion; $x_2 =$ Agreeableness; $x_3 =$ Conscientiousness; and $x_4 =$ Neuroticism.

In addition, it has been pointed out that LR generally has a relatively simple mathematical structure compared with non-linear techniques such as FNN [95]. Such simple structure may lead to instability of the regression equations, being sensitive to potential structural breaks in the input signals [74]. A structural break refers to an abrupt shift in the slope of a trend line over a series of data points. To ascertain the structural stability of the LR formulas (5) and (6), a widely used approach—Chow test—was adopted. The Chow test can estimate whether the parameters of a LR model are structurally stable, and runs as follows [92]: 1. Identifying the structural breaks in the dataset used to develop the model and splitting the dataset into subsets at the breakpoints; 2. Performing separate regressions on the entire dataset and each subset of the data; 3. Retreiving the residual sum of squares for each regression; and 4. Computing the Chow statistic using the formula:

$$F = \left( \frac{(N-2k)}{k} \right) \frac{R_w - \left( \sum_{j=1}^{n} R_j \right)}{\sum_{j=1}^{n} R_j}$$

where $F =$ the Chow statistic; $R_w =$ residual sum of squares of the regression for the whole dataset; $n =$ the number of sub-datasets split according to structural breaks; $j =$ the $j^{th}$ sub-dataset; $R_j =$ residual sum of squares of the regression for the $j^{th}$ sub-dataset; $N =$ the number of samples in the whole dataset ($N =$ 228, including 188 training samples and 40 validating samples as assigned in Section 3.1.4); and $k =$ the number of input variables ($k =$ 4, including four personality traits).

The Chow test was conducted using the computer programme SAS [92]. The results showed that there was one structural break in the whole dataset, resulting in two split sub-datasets and the following $R_w$, $R_1$ and $R_2$ for the LR formulas (5) and (6) respectively: 33.497, 18.143, and 15.136 ($p < 0.001$); 82.325, 39.693, and 41.667 ($p < 0.001$). Applying the formula (7) above, the $F$ values were computed respectively for the LR formulas (5) and (6) as follows: 0.37 ($p < 0.001$) and 0.65 ($p < 0.001$). According to the criteria of Chow test [92], the parameters of a LR model are considered structurally stable when the calculated $F$ value is less than the $F$-critical value with $(k, N-2k)$ degrees of freedom which can be retrieved from the $F$-distribution table (available online at: www.stat.purdue.edu/~jtroisi/STAT350Spring2015/tables/FTable.pdf). As predefined, the values of $k$
and $N$ equal to 4 and 228 respectively. The degrees of freedom for the $F$-critical value is thereby determined as (4, 220). According to the $F$-distribution table, the $F$-critical value with degrees of freedom (4, 220) and $p$-value less than 0.001 is 4.81. The calculated $F$ values, 0.37 ($p < 0.001$) and 0.65 ($p < 0.001$) are therefore well below the $F$-critical value 4.81 ($p < 0.001$), which indicates that the parameters of the LR formulas (5) and (6) are structurally stable.

4 Results and Discussion

4.1. Comparing the Prediction Accuracy of the Machine Learning and Linear Regression Models

After determining the architecture of the ML and LR models, the prediction accuracy was tested on the testing dataset. The results are given in Figure 4, showing a comparison between the predicted results (ML and LR) and actual results on both task performance and contextual performance for all the testing samples. The horizontal axis of the plot outlines 40 samples in the testing dataset, and the vertical axis represents one’s score on task performance and contextual performance, where a higher score indicates a greater performance in terms of behaving safely at work.

Fig. 4. Predicted-Actual Plot (Task Performance and Contextual Performance)
Based on the predicted-actual plot, the prediction accuracy was evaluated using the statistical parameter generalisation error ($E_{gen}$), which is a measure of how accurately a mathematical model is able to make predictions for previously unseen data [18]. The $E_{gen}$ can be calculated using the formula below, where a value less than 0.25 is considered a low level of error as well as a satisfactory level of prediction accuracy [91]:

$$E_{gen} = \frac{1}{n} \sum_{m=1}^{n} (Y_m - \hat{Y}_m)^2$$

where $E_{gen}$ = generalisation error; $n$ = the number of samples in the testing dataset; $Y_m$ = the actual result for the $m^{th}$ sample; $\hat{Y}_m$ = the predicted result for the $m^{th}$ sample.

In our case, the $E_{gen}$ rates were 0.14 and 0.24 for ML predictions on task performance and contextual performance respectively. According to the threshold (below 0.25), the prediction accuracy of the developed ML model is satisfactory. In addition, the $E_{gen}$ rates were 0.20 and 0.53 for LR predictions on task performance and contextual performance respectively. Given the threshold (below 0.25), the prediction accuracy of the developed LR formulas is satisfactory for task performance but unsatisfactory for contextual performance. In a comparison of the $E_{gen}$ rates of the ML model and LR formulas as presented above, the results showed that the LR method demonstrated greater errors than the ML method for the prediction of both task performance and contextual performance. This implies that a nonlinear relationship may exist between construction workers’ personality traits and safety behaviour as the LR method was unable to fully capture the personality-safety behaviour relationship and yielded greater prediction errors.

As also presented above, the error rate for the ML prediction of contextual performance was greater than task performance. This suggests that the developed ML model may have a better prediction accuracy for task performance than contextual performance. One possible explanation lies in the fact that the scale for measuring task performance (eight items) is larger than contextual performance (three items) (see Appendix C). A greater number of measurements taken and data points included in the average can diminish the influence of unexpected noise in data [25].

4.2. Relative Importance Analysis

Unlike the explicit nature of LR, ML techniques are often viewed as “black box” because they allow little insights into the relations that are used to predict the output variables [36]. For example, the
weights in the LR formulas (5) (6) (Section 3.2) indicate the relative importance of each input variable for their relations to the output variable [4], whereas such information is not demonstrated directly in the ML formulas (1) (2) (3) (4) (Section 3.1.6). To open the “black box”, the relative importance analysis method has been proposed by Garson [32] to analyse the relative importance of each input variable. This method has been successfully used by many researchers and has been proven to be highly effective and reliable [e.g., 59, 88]. In order to provide more insights into the ML model after its development, the relative importance analysis was performed applying the following algorithm suggested by Garson [32]:

\[ RI_{j,i} = \frac{\sum_{k=1}^{N_j} \left( \left| w_{j,k}^{IH} \right| \sum_{j=1}^{N_i} \left| w_{j,k}^{IH} \right| \times \left| w_{k,j}^{HO} \right| \right)}{\sum_{j=1}^{N_j} \sum_{k=1}^{N_k} \left( \left| w_{j,k}^{IH} \right| \sum_{j=1}^{N_i} \left| w_{j,k}^{IH} \right| \times \left| w_{k,j}^{HO} \right| \right)} \]  

(9)

where \( RI_{j,i} \) = the relative importance of the \( j \)\(^{th} \) input variable on the \( i \)\(^{th} \) output variable; \( j \) refers to both the \( j \)\(^{th} \) input variable and the \( j \)\(^{th} \) input neuron (each input neuron corresponds to one of the input variables); \( N_j \) = the total number of input neurons; \( N_k \) = the total number of hidden neurons; the definitions and values of \( w_{j,k}^{IH} \) and \( w_{k,j}^{HO} \) can be found in Table 3.

The computed values of relative importance are given in Table 4 below. As can be seen, conscientiousness with the relative importance of 38.19% and 40.59% indicated the strongest relations with task performance and contextual performance and appeared to be the most influential input parameter. This result is consistent with the findings of several previous studies [e.g., 23, 87, 103]. As shown in their studies, conscientiousness demonstrated the strongest relationship with employees’ safety behaviour among the Big Five traits. One possible explanation for this finding may lie in the nature of conscientiousness itself. Conscientiousness is the personality trait of being responsible while extraversion, agreeableness and neuroticism indicate how outgoing, friendly and emotionally stable a person is [49]. The responsible-oriented nature of conscientiousness leads individuals to be responsible for their own well-being and behave safely at work [98]. Such personality trait would result in the highest involvement in safety behaviour compared with extraversion, agreeableness and neuroticism [87].
### Table 4. Relative Importance of Input Variables on Output Variables

| Input Variables | Relative Importance on Output Variables (%) |
|-----------------|---------------------------------------------|
|                 | Task Performance | Contextual Performance |
| Extraversion    | 11.29            | 18.49                  |
| Agreeableness   | 32.58            | 24.85                  |
| Conscientiousness | 38.19           | 40.59                  |
| Neuroticism     | 17.94            | 16.08                  |

In addition, the other personality traits also exhibited certain levels of importance for their relations to workers’ safety behaviour, with the relative importance values being 32.58% and 24.85% for agreeableness, 17.94% and 16.08% for neuroticism, and 11.29% and 18.49% for extraversion. Previous studies have provided insights as to why these personality traits and workers’ safety behaviour might be related. Beus, et al. [10] pointed out that safety behaviour is the function of individuals to attain certain goals (e.g., status, communion, and self-control) at work, which is driven by personality factors. For example, extraversion is associated with the goal of status, and individuals with a high level of extraversion are more likely to work unsafely (e.g., taking shortcuts, ignoring safety rules) to become productive and sustain competitive advantages over their colleagues. Agreeableness is associated with the goal of communion, and individuals with a high level of agreeableness should be less likely to perform unsafely as unsafe behaviours may put their colleagues’ well-being at risk and then damage interpersonal relationships as a result. Neuroticism is associated with the goal of self-control, and individuals with a high level of neuroticism tend to have poor self-control and more negative emotions, which may result in distracted thinking and then affect safety behaviour.

### 5 Conclusions

In this paper, the authors developed two mathematical models for the prediction of construction workers’ safety behaviour based on personality traits using machine learning (ML) and linear regression (LR) techniques respectively. Using the configuration of four input variables for personality traits (i.e. extraversion, agreeableness, conscientiousness, and neuroticism) and two output variables for safety behaviour (i.e. task performance and contextual performance), the ML model—a feedforward neural network based on the Levenberg–Marquardt back-propagation algorithm—was developed, which can be represented by its mathematical expressions (1) (2) (3) (4) as shown in Section 3.1.6. The developed ML model is demonstrated to predict reasonably well. According to the results obtained on the testing dataset (see Section 4.1), it achieved low error rates on the prediction of task performance and
contextual performance. The good prediction accuracy obtained provides the empirical evidence to support the usefulness of personality traits as effective predictors in explaining people’s safety behaviour at work.

The results also showed that the LR method demonstrated greater errors than the ML method for the prediction of both task performance and contextual performance (see Section 4.1). This implies that a nonlinear relationship may exist between construction workers’ personality traits and safety behaviour as the LR method was unable to fully capture the personality-safety behaviour relationship and yielded unsatisfactory prediction accuracy. As previous studies in this field all utilised the LR method to establish the predictive relationship between construction workers’ personality and safety behaviour [e.g., 90], our study is potentially the first to provide: 1. empirical evidence suggesting that nonlinearity may exist in the relationship between construction workers’ personality traits and safety behaviour; 2. empirical evidence to support the utility of ML over LR for the prediction of construction workers’ safety behaviour using personality factors; and 3. a more reliable estimate of the predictive relationship between construction workers’ personality traits and safety behaviour.

This study highlights the role of behaviour prediction in promoting workplace safety and is designed to offer practical implications for the safety management on construction sites. As mentioned, a prior prediction on employees’ safety behaviour is useful in the identification of the weaknesses in organisations. The ML model developed in this study is proven to have good prediction accuracy and is therefore recommended as a potential prediction tool for decision making. Site managers can input data on workers’ personality traits and the ML model will estimate and output the possible results on safety behaviour for consideration. The developed ML model is also capable of giving dual outputs on safety behaviour, namely, task performance and contextual performance. This can be useful in identifying potential undesirable aspects in different individuals in order to provide appropriate remedial measures for people with different needs. For example, individuals scored low on task performance are more likely to conduct non-compliance behaviours such as taking shortcut, not using of safety equipment, and violating safety procedures and rules. With these, site managers may adopt interventions to enhance their sense of discipline and compliance. For those who scored low on contextual performance tend to be reluctant to conduct voluntary safety activities such as reporting safety problems, keeping workplace clean, and caring for colleagues’ safety. Site managers may therefore employ incentive methods to promote their desire to make contributions to workplace safety.
Although the developed ML model has been shown to have practical implications, this study presents certain limitations that warrant further research. The prediction accuracy of the developed ML model was evaluated using workers’ self-reported data on safety behaviour scales (Appendix C refers). However, in practice, the self-report measures are found to be frequently adopted by researchers to collect behavioural data from construction workers [e.g., 37,90] because it is always risky to expose researchers to workers’ operating environment for behaviour observation considering the hazardous nature of construction sites [30]. Considering the good ecological validity of virtual reality in the evaluation of human behaviours and the fact that virtual reality can provide a safe environment for experimentation [54], virtual reality technology may be adopted to develop a safe strategy to observe construction workers’ safety behaviour and evaluate the prediction accuracy of the developed ML model on workers’ safety behaviour observed.

6 References

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Appendix A: The Big Five Inventory

Please indicate the extent to which you agree with the following statements (disagree strongly, disagree a little, neither agree nor disagree, agree a little, agree strongly).

I see myself as someone who…

Q1: is talkative. (a)
Q2: tends to find fault with others. (b)
Q3: does a thorough job. (c)
Q4: is depressed. (d)
Q5: is original, comes up with new ideas. (e)
Q6: is reserved. (a)
Q7: is helpful and unselfish with others. (b)
Q8: can be somewhat careless. (c)
Q9: handles stress well. (d)
Q10: is curious about many different things. (e)
Q11: is full of energy. (a)
Q12: starts quarrels with others. (b)
Q13: is a reliable worker. (c)
Q14: can be tense. (d)
Q15: is ingenious, a deep thinker. (e)
Q16: generates a lot of enthusiasm. (a)
Q17: has a forgiving nature. (b)
Q18: tends to be disorganised. (e)
Q19: worries a lot. (d)
Q20: has an active imagination. (e)
Q21: tends to be quiet. (a)
Q22: is generally trusting. (b)
Q23: tends to be lazy. (c)
Q24: is emotionally stable. (d)
Q25: is inventive. (e)
Q26: has an assertive personality. (a)
Q27: can be cold and aloof. (b)
Q28: perseveres until the task is finished. (c)
Q29: can be moody. (d)
Q30: values artistic, aesthetic experiences. (e)
Q31: is sometimes shy. (a)
Q32: is considerate and kind to almost everyone. (b)
Q33: does things efficiently. (c)
Q34: remains calm in tense situations. (d)
Q35: prefers work that is routine. (e)
Q36: is outgoing. (a)
Q37: is sometimes rude to others. (b)
Q38: makes plans and follows through with them. (e)
Q39: gets nervous easily. (d)
Q40: likes to reflect, play with ideas. (e)
Q41: has few artistic interests. (g)
Q42: likes to cooperate with others. (b)
Q43: is easily distracted. (c)
Q44: is sophisticated in art, music, or literature. (e)

(a) Extraversion; (b) Agreeableness; (c) Conscientiousness; (d) Neuroticism; (e) Openness.
Appendix B: The Work-specific Big Five Inventory

Please indicate the extent to which you agree with the following statements (disagree strongly, disagree a little, neither agree nor disagree, agree a little, agree strongly).

I see myself as someone who...

Q1: is talkative at work. (a)
Q2: tends to find fault with others at work. (b)
Q3: does a thorough job at work. (c)
Q4: is depressed at work. (d)
Q5: is reserved at work. (a)
Q6: is helpful and unselfish with others at work. (b)
Q7: can be somewhat careless at work. (c)
Q8: handles stress well at work. (d)
Q9: is full of energy at work. (a)
Q10: starts quarrels with others at work. (b)
Q11: is a reliable worker at work. (c)
Q12: can be tense at work. (d)
Q13: generates a lot of enthusiasm at work. (a)
Q14: has a forgiving nature at work. (b)
Q15: tends to be disorganised at work. (c)
Q16: worries a lot at work. (d)
Q17: tends to be quiet at work. (a)
Q18: is generally trusting at work. (b)
Q19: tends to be lazy at work. (c)
Q20: is emotionally stable at work. (d)
Q21: has an assertive personality at work. (a)
Q22: can be cold and aloof at work. (b)
Q23: perseveres until the task is finished at work. (c)
Q24: can be moody at work. (d)
Q25: is sometimes shy at work. (a)
Q26: is moody at work. (a)
Q27: does things efficiently at work. (c)
Q28: remains calm in tense situations at work. (d)
Q29: is outgoing at work. (a)
Q30: is sometimes rude to others at work. (b)
Q31: makes plans and follows through with them at work. (c)
Q32: gets nervous easily at work. (d)
Q33: likes to cooperate with others at work. (b)
Q34: is easily distracted at work. (c)

(a) Extraversion; (b) Agreeableness; (c) Conscientiousness; (d) Neuroticism.

Appendix C: The Safety Behaviour Scale

Please indicate the extent to which you agree with the following statements (disagree strongly, disagree a little, neither agree nor disagree, agree a little, agree strongly).

I see myself as someone who...

Q1: overlooks safety procedures in order to get my job done more quickly. (a)
Q2: follows all safety procedures regardless of the situation I am in. (a)
Q3: handles all situations as if there is a possibility of having an accident. (a)
Q4: wears safety equipment required by practice. (a)
Q5: keeps workplace clean. (b)
Q6: encourages co-workers to be safe. (b)
Q7: keeps my work equipment in safe working condition. (a)
Q8: takes shortcuts to safe working behaviours in order to get the job done faster. (a)
Q9: does not follow safety rules that I think are unnecessary. (a)
Q10: reports safety problems to my supervisor when I see safety problems. (b)
Q11: corrects safety problems to ensure accidents will not occur. (a)

(a) Task Performance; (b) Contextual Performance.