Uncorrected final draft of:

Karanika-Murray, M., & Cox, T. (2010). The use of Artificial Neural Networks and Multiple Linear Regression in modeling work-health relationships: Translating theory into analytical practice. European Journal of Work & Organisational Psychology, 19(4), 461-486. doi: 10.1080/13594320902995916

The Use of Artificial Neural Networks and Multiple Linear Regression in Modeling Work-Health Relationships: Translating Theory into Analytical Practice

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Short title: Modeling work-health relationships

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Keywords: artificial neural networks, linear regression, linearity assumption, nonlinear relationships, work-related health

Abstract

Although psychological theory acknowledges the existence of complex systems and the importance of nonlinear effects, linear statistical models have been traditionally used to examine relationships between environmental stimuli and outcomes. The way that we analyze these relationships does not seem to reflect the way that we conceptualize them. The present study investigated the application of connectionism (artificial neural networks) to modeling the relationships between work characteristics and employee health by comparing it with a more conventional statistical linear approach (multiple linear regression) on a sample of 1003 individuals in employment. Comparisons of performance metrics indicated differences in model fit, with neural networks to some extent outperforming the linear regression models, such that R^2 for worn-out and job satisfaction were significantly higher in the neural networks. Most importantly, comparisons revealed that the predictors in the two approaches differed in their relative importance for predicting outcomes. The improvement is attributed to the ability of the neural networks to model complex nonlinear relationships. Being unconstrained by assumptions of linearity, they can provide a better approximation of such psychosocial phenomena. Nonlinear approaches are often better fitted for purpose, as they conform to the need for correspondence between theory, method and data.

The Use of Artificial Neural Networks and Multiple Linear Regression in Modeling Work-Health Relationships: Translating Theory into Analytical Practice

Modeling the impact of work and organizational characteristics on employee health is important in terms of decision-making for job design, re-design and organizational development. Effective management of work-related health relies on accurately prioritizing potential risks and explaining the highest variability in outcomes from a combination of work and organizational characteristics (Clarke & Cooper, 2004; Cox *et al.*, 2000; Glendon, Clarke, & McKenna, 2006). In turn, this traditionally relies on correlational and linear approaches. Although such an approach has historically proven useful, it produces two sources of uncertainty for the assessment of risk to work-related health. First, it implies a linear relationship between work and organizational characteristics and health outcomes, which often conflicts with available empirical evidence (Karanika, 2006). Second, organizations themselves provide a demonstration of complexity (Cox *et al.*, 2007; Schneider & Somers, 2006). It also renders examination of the impact of combinations of risks (as opposed to bivariate relationships) more pertinent to decision-making in relation to risk management for work-related health (Karanika-Murray, Antoniou, Michaelides, & Cox, *in press*). The present study tested a nonlinear connectionist model vis-à-vis a traditional linear regression model of the impact of work characteristics on work-related outcomes. The remainder of this section discussing two key sources of uncertainty in modeling work-health relationships which set the main arguments for artificial neural networks, before it briefly outlines their principles.

Uncertainty 1: Nonlinear Work-Health Relationships

The first source of uncertainty in examining work-health relationships relates to underlying assumptions. A focus on potential nonlinear relationships is theoretically justified and empirically supported. Optimal levels of work-related health and performance away from extreme levels of work characteristics have often been proposed (e.g., Jamal, 1985; McGrath, 1976; Muse, Harris, & Feild, 2003). Expectations of nonlinear relationships between work and health, well-being, and performance can be traced in established theoretical models such as the General Adaptation Syndrome (Selye, 1975), the Person-Environment Fit model (Edwards, Caplan, & Harrison, 1998), and the Vitamin Model (Warr, 1987). Elements of curvilinearity, nonlinearity, complexity, homeostasis and a systems approach to understanding occupational health have been implicitly and explicitly incorporated in this theoretical repository. Empirical evidence has also accumulated that describes the effects of work and organizational characteristics on employee health as nonlinear (e.g., Borg, Kristensen, & Burr, 2000; de Jonge & Schaufeli, 1998; Rydstedt, Ferrie, & Head, 2006; Zivnuska *et al.*, 2002). Furthermore, a state-of-the-art review of research on the relationships between work-related stressors and their effects concluded that the nature of these relationships is dynamic, nonlinear and discontinuous, but also stressed that only a very small percentage of the reviewed literature examined nonlinear relationships explicitly (Rick, Thomson, Briner, O'Regan, & Daniels, 2002). Additionally, explicit comparisons of linear and nonlinear analytical approaches have shown that the fit of the latter is better than that of the former; nonlinear models can explain more variance in outcomes compared to their linear equivalents (e.g., Lowe *et al.*, 2003).

The practice of occupational health psychology and, specifically, the area of risk management, draw heavily on this theoretical and methodological position. Most of the analytical techniques predominantly used in social science research are inferential statistical approaches based on the general linear model (Trochim, 2000) that assume continuous linear relationships between variables, invariably allowing for some error. This is underlined by an implicit assumption of stable linear relationships which, as many have noted, lies at the heart of social science research. Typically used are linear methods such as odds ratio, linear regression, correlation, and so on.

However, some dissatisfaction with the 'permeating' linearity assumption and the use of convention linear models approaches has been overtly expressed in sociological research (e.g., Abbott, 1988), human resource management (e.g., Mendenhall, Macomber, Gregersen, & Cutright, 1998), and occupational health research (e.g., Ferris *et al.*, 2006). Most characteristically, Guion (1989) opposes the 'procrustean approach' to research, where the development of theory is often confined to available methods of mainstream paradigms. Linear static relationships often exist and can be studied using linear methods. When nonlinear relationships are probable, however, linear tools will constitute weak approaches (Karanika, 2006). Indeed, empirical support for nonlinear relationships has been inconsistent (Ferris *et al.,* 2006; Muse *et al.*, 2003), leading researchers to suggest that this might be due to studying potentially nonlinear relationships with linear methods (e.g., Guion, 1992; Somers, 2001).

Uncertainty 2: Organizational Complexity

A second source of uncertainty in examining work-health relationships resides in the complexity and changing nature of organizational reality (Cox *et al.*, 2007; Ovretveit, 1998). Organizations are often described as complex adaptive systems within which occupational health issues are embedded (Dooley, 1997; Schneider & Somers, 2006). This complexity is illustrated by the difficulty in conducting organisational interventions. It also often renders attempts to describe the exact relationships between a specific predictor and an outcome impractical for risk assessment in organizational settings. Rather, the overall pattern, impact and relative importance of multivariate work-related risks is of higher relevance for discerning the underlying organizational pathology and for risk management. Improved decision-making for occupational health management can only rely on accurate assessment of the impact of work on health. The premise that relationships between work characteristics and employee health are not necessarily linear and the concern that traditional approaches may be inadequate for risk management provide an impetus for exploring alternatives. This is especially useful in situations where the form of the relationships between a specific work characteristics and an outcome is of lesser importance for risk management than the ability to explain as much of the variance in the outcomes as possible from a range of work characteristics.

The implications of resolving these uncertainties for the management of work-related health are evident. Explicitly incorporating multivariate curvilinear effects of work on health in risk estimation has been shown to provide more accurate models which can be used for the risk management (Karanika-Murray *et al.*, *under review*). Different techniques are appropriate for different purposes and researchers should be explicit in their choices. Given that nonlinear relationships exist and that our knowledge has outgrown the linearity assumption, it would be useful to explicitly compare the performance of one technique which is the common choice for prediction with another which is also suited for complex nonlinear phenomena.

An Alternative Approach

A multitude of methods for the study of nonlinear systems are available and have been applied to psychological research (Barton, 1994; Eidelson, 1997). For example, polynomial regression is commonly used for examining curvilinear effects (e.g. de Jonge & Schaufeli, 1998; Rydstedt *et al.*, 2006; Zivnuska *et al.*, 2002), whereas computer simulations have also been used for exploring nonlinearity (Somers, 2001). An alternative that is proving well-suited for capturing nonlinearity is connectionism, or artificial neural networks. It has been surmised that neural networks are better at examining nonlinearity than conventional statistical approaches (Collins & Clark, 1993; Hanges et al., 2001). Connectionism has been used in applied areas such as workplace behavior (Collins & Clark, 1993), employee turnover (Somers, 1999), motivation theory (Lord *et al.*, 2003), health behavior (Lowe *et al.*, 2003), and cancer prognosis (Sargent, 2001). Although their uptake in disciplines such as engineering, physics, economics, neurobiology, cognitive psychology, and medicine has been rapid, they have been sparingly used elsewhere (Somers, 1999). Organizational research has sought to establish their predictive efficacy over conventional statistical methods, making them a popular decision-making tool in applied settings (DeTienne, DeTienne, & Joshi, 2003; Scarborough & Somers, 2006; Somers, 2008). Although not yet examined in this direction, artificial neural networks may also prove to be of use in the assessment and management of risks to work-related health.

Artificial Neural Networks – A Brief Introduction

The seeds of connectionism were planted by James (1890s), McCulloch and Pitts (1940s) and Hebb (1940s) and their work on the biological neuronal structure of the brain, correlational learning and associative memory (Posner & Rothbart, 2004). Its computational properties (the neural network structure) were first delineated by Rosenblatt in 1958 (Eberhart & Dobbins, 1990). Interconnected neurons or nodes receive input that determines the output that they dispatch to other nodes, and the network learns by strengthening the connections between nodes (Smith, 1996). This section provides a brief account of neural networks. The reader can refer to available excellent insights into their technical elements and applications (e.g., McClelland & Rumelhart, 1986; Rumelhart & McClelland, 1986).

A neural network consists of: (1) an *input layer* of simple nodes or processing units that receive external stimuli, (2) a *hidden layer* of units (similar to adaptors) that store relationships between the input and output layers and (3) an *output layer* of outcome units (see Figure 1). These are arranged so that each unit in one layer receives signal from each unit in the preceding layer through their *synapses*, which store their *activation*. Activation is a function of the unit's summed inputs and depends on the strength of the output, the weights linked to each unit, as well as a transformation function (Anderson & McNeill, 1992; Curry, Morgan, & Silver, 2002). Each node multiplies the incoming signals by the weight of their connection, sums these, rescales the total (a value from 1 to 0) and transfers the signal to the next layer.

(Figure 1 about here)

Learning (and weight adjustment) takes place in an iterative manner, as node activation occurs. The network weights contain the *memory* of the system. Each network starts with a set of random weights which, via the synapses, are fed forward through the system. The observed or actual values of the output or outcome variable are compared with those predicted on the basis of these weights. The weights are then adjusted to minimize the error between actual or observed and predicted values or the discrepancy between the input signal and a goal or comparison value. This *dissonance minimization function* bears similarity to the feedback mechanism of self-regulatory behavior (see Carver & Scheier, 1998). A number of learning algorithms have been developed, the most popular being the *backpropagation* method (Eberhart & Dobbins, 1990). Activation that feeds forward through the network from input to output units and where nodes in one layer are not allowed to be linked with each other, describes a feedforward network. Nodes that are more densely interconnected so that both feedforward and feedback of activation is possible are called recurrent networks. More complex architectures can be constructed by incorporating feedforward and recurrent modules. Neural network learning can be supervised, where target outputs are known and the network is required to develop a model that best fits the data or target model, or unsupervised, where output values are unknown and the network is required to detect patterns of similarity within a given set of inputs. Supervised learning is analogous to statistical multiple linear regression and discriminant analyses (Sarle, 1994; Smith, 1996), where input variables are used to predict values or categories of a target output variable (a network with no hidden layers and a linear activation function). Unsupervised learning, on the other hand, can be compared to statistical data reduction techniques (e.g., factor analysis).

The main advantage s of neural networks are their (1) adaptability, (2) ability to learn using trial and error, (3) nonlinear approach and (4) ability to model highly dimensional data

(Karanika, 2006). Inclusion of multiple hidden layers and nodes allows for more complexity in the network's architecture (Sarle, 1994). Connectionism is also referred to as parallel distributed processing (PDP): parallel because it happens simultaneously and distributed because each element or node can participate in more than one pattern of representations at the same time. PDP is one of the most important attributes of connectionist models. It allows neural networks to exhibit contextual sensitivity at 'a fine-grained level' (Lord, Hanges, & Godfrey, 2003). There is no direct discernible relationship between local nodes (lower level processing) and the global pattern or representation (higher level meaning) between inputs and output. Rather, the final models emerge from the pattern of activation. Thus, knowledge on the complexity of the system is contained in the network architecture and the pattern of interconnections, rather than in the exact relationships between predictors and outcomes.

It has often been suggested that neural networks are better at examining nonlinear phenomena than conventional statistical approaches (e.g., Collins & Clark, 1993; Hanges et al., 2001; Lowe et al., 2003; Somers, 1999). Statistics and neural networks differ in three fundamental respects which provide the impetus for using neural networks in the present study. First, conventional statistics are based on the general linear model and its underlying assumptions on normally distributed data, aggregativity, temporal effects, independence of variables, and so on (underlying assumptions). Second, in neural network modeling concepts of complexity, nonlinearity and systems are evoked at the network architecture level by virtue of its PDP capacity (systems, complexity and nonlinearity). Finally, where error or noise is a problem in statistical analyses, neural networks are able to adapt to it (contextual sensitivity). Curry et al. (2002) note that although neural networks can be "forced to have a linear component, the linear case is effectively nested within a larger and more flexible specification" (p. 964). Thus, complexity and nonlinearity are embedded in the network's architecture rather than the exact relationships between variables, thus allowing for a supple conceptualization of complex phenomena. On the negative side, many have described neural networks as a 'black box' approach (Paruelo & Tomasel, 1997; Price et al., 2000): it is not possible to discern the relationships between a specific predictor and the outcome in a neural network, in the same way that statistical formulae allow. However, as mentioned, this is often neither necessary in occupational health risk assessment nor feasible in organizational settings. Neural networks' utility for the assessment and management of work-related health lies in the fact that they can be used as a decision-making tool.

The Present Study

The present study explored the application of artificial neural networks in modeling the relationships between work and organizational characteristics and employee health outcomes. It is grounded on the observation that the way that we use to analyze work-health relationships does not reflect the way that we conceptualize such relationships.

Any new approach introduced in a well-defined area should be compared to existing methods (Chatfield, 1993). Multiple linear regression was used to estimate the linear models and as a baseline for comparing neural network performance. Polynomial linear regression analysis as used for examining curvilinear relationships was rejected because (a) it looks at curvilinearity but not nonlinearity, (b) it introduces curvilinearity by the quadratic term of the predictor within a linear combination of predictors (EMBED Equation.3 ☐), which is essentially an intrinsically linear approach (DeTienne et al., 2003). True nonlinear models express nonlinearity in the parameters of the variables. Additional shortcomings of linear regression (Bansal et al., 1993; Lind & Sulek, 2001; Lowe et al., 2003) render it inappropriate for addressing nonlinear phenomena.

The present study compared an inherently linear (multiple linear regression) and an inherently nonlinear method (artificial neural networks). It focused on two neural networks with one output, whose aim was to predict an outcome by learning the associations between that variable and a set of inputs. It was expected that (a) there would be differences in variance explained between the linear and the nonlinear approaches, and (b) the relative positioning of the variables or the architecture of the models would differ in the linear and nonlinear models. Job satisfaction and worn-out (or symptoms of fatigue and exhaustion) are commonly used in risk assessment for work-related health and were used here as outcomes in separate models. Different aspects of work-related health are differentially associated with work characteristics and should thus be examined separately (Warr, 1990).

Method

Participants and Procedure

This study used data obtained from risk assessment studies carried out for the UK Health and Safety Executive and the European Commission over the last two decades (see Cox *et al.*, 2000). The data came from 5 organizations covering a number of sectors and focusing on a multitude of work characteristics across a variety of job roles (e.g., retail staff, customer services staff, and warehouse staff). In the original studies, all staff across all departments in the organizations were asked to participate. Mean response rate was 54%, with a range of 48% to 62%. For the present study, the data were combined into a larger dataset of $N = 1003$, which provided a satisfactory sample size for the models. Outliers were identified and removed prior to the analyses. The predictors included in the models were: employee characteristics (gender, age, tenure, social support) and work characteristics (see below). Outcomes were job satisfaction and worn-out. Table 1 presents the descriptive statistics before substitution of missing values (see below). The final sample consisted of 53.4% ($n = 531$) males and 46.6% ($n = 463$) females. Participants' age ranged from 17 to 65 years ($M = 37.42$, $SD = 10.76$). Tenure in the organization ranged from <1 to 41 years ($M = 9.95$, $SD = 8.53$).

(Table 1 about here)

Measures

Age, *gender* and *tenure* have been related to employee health and work attitudes (e.g., Clark, Oswald, & Warr, 1996; Siu, Spector, Cooper, & Donald, 2001). As a binary variable, gender can be used in multiple linear regression (see Tabachnick & Fidell, 2001) and was thus included in the models.

Social support was measured by asking respondents to indicate whether or not they would be happy to discuss personal work problems with any of a number of sources. The number of sources of social support used was summed into a single item, with a high score indicating use of more sources of social support for work problems.

Work characteristics. In the original studies a list of items describing aspects of work and working conditions was identified from the information collected during interviews, familiarization visits, and focus groups. Where necessary, this information was supplemented with available scientific evidence to provide complete coverage of work characteristics (see Cox, 1993, 2000). Employees were asked to judge the adequacy of their work using their knowledge of their work to complete a survey assessing experienced work and organizational issues (1 = unacceptable/very unsatisfactory, 4 = excellent/very satisfactory). In combining the data for the present study, the most prevalent work characteristics were selected. Items as opposed to factor-analyzed work characteristics were used. Because respondents were asked to rate only the items that applied to their work the number of missing data was high. It was necessary to retain a large sample size for the analyses in order to minimize the need for missing data estimation for both the regression models and the neural networks. Therefore, the items with no more than 10% missing data (in both cases and variables) which were common across all samples were chosen: communication with manager, relationships with colleagues, job security, teamwork, staffing, initial training, facilities (for taking breaks), decision latitude, time for training, number of breaks taken, others' knowledge (about one's job), equipment suitability, home-work support, manager demands. These work characteristics represent the range of work issues identified in the literature that can impact on individual health (see Cox, Griffiths, & Rial-González, 2000; Cox, Karanika-Murray, Griffiths, Wong, & Hardy, 2009).

The *worn-out* scale of the *General Well-being Questionnaire* (Cox, Thirlaway, Gotts, & Cox, 1983), a self-report symptom-based measure of sub-optimal health was also used. Worn-out is described by symptoms relating to fatigue, emotional lability and cognitive confusion and is measured by 12 items. Respondents are asked to indicate how often they have experienced a number of symptoms ('become easily annoyed or irritated', 'had difficulty in falling or staying asleep') in the last 6 months (0 = never, 4 = all the time; higher scores indicating lower worn-out). Reliability was $\alpha = .88$ (N = 977).

Job satisfaction was assessed by asking respondents to indicate how satisfied they were with their job (0 = not at all satisfied, 4 = very satisfied) ($M = 2.21$, $SD = 1.02$). A one-item global rating is a reliable measure of general job satisfaction (mean $r = .67$ between one and multiple item scales have been reported; Nagy, 2002; Wanous, Reichers, & Hudy, 1997).

Some of the work characteristics were slightly skewed. Although neural networks do not require the data to be normally distributed, normality is one of the key assumptions for linear regression. With large datasets a non-normal distribution does not have an impact on the results, such that 'in a large sample, a variable with statistically significant skewness does not deviate enough from normality to make a substantive difference in the analyses' (Tabachnick & Fidell, 2001, p. 74). The job characteristics were therefore retained untransformed. Of the remainder variables, only age was transformed (see below).

The Worn-out and Job Satisfaction Networks

The neural network literature provides limited guidance on required sample size (Price *et al.*, 2000) and optimal numbers of hidden layers and of hidden nodes (Anderson & McNeill, 1992). Estimations are based on the basis of considerations such as data noisiness (errors or imperfections) and model complexity. Since we were unsure of the noisiness of the data and because more hidden layers and/or hidden nodes can help networks learn more complex relationships, it was decided to train one- and two-hidden layer supervised networks with 9 to 18 hidden nodes each, proportionate to the number of predictors.

A small level of data missing at random is acceptable for traditional multivariate statistics (Tabachnick & Fidell, 2001). However, neural networks do not tolerate any missing data. Missing values were estimated by the Expectation Maximization method (Hsiao, 1980). Missing values for gender were substituted on the basis of the distribution of males and females. Steps were taken to help the network escape from partial solutions in response to the data (local minima) during learning or training. Training was more accurate with higher values, thus the term used for updating the weights during training was set to .9 (*alpha;* can range from 0 to 1). A moderate rate of change of weight adjustment (*eta;* can range from .10 to .01) at each update was selected, in order to help detect variables that contributed significantly and were thus more influential for learning. The values used to initialize the *network weights* were set to random. Finally, overfitting a network to the data (or overtraining) should be avoided as it inhibits generalizability of the network to new data (DeTienne *et al.*, 2003; Makridakis, Wheelwright, & Hyndman, 1998). A convention is to divide the data randomly into training and cross-validation (80-20%) sets. This yielded a neural network training sample of 802 and a validation sample of 201.

Results

Correlations, means and standard deviations for all variables are presented in Table 1. The minimum correlation for a statistical power of .80 ($N = 1003$, $p < .05$) in the present sample was $r = .09$ (Cohen, 1988).

Artificial Neural Network Modeling

One-output supervised feedforward neural networks were trained for prediction, separately for worn-out and job satisfaction, using the backpropagation learning method. Networks with one and two hidden layers were trained and validated on known output data. SPSS Clementine was used, which provides a powerful graphical interface to implement the neural networks. Table 2 presents training accuracy for the best models, predictors included and their *Relative Importance* (RI), correlations between measured and predicted values and *Mean Absolute Percentage Error* (MAPE) for the worn-out and job satisfaction networks. Accuracy of 80-90% is considered good. RI is an effect size metric that incorporates a summary of the weights of the inputs (Lucek & Ott, 1997). It indicates the influence of a predictor in relation to all predictors included in the model. MAPE is based on the error between actual and predicted values (such that MAPE = $\Sigma|pe|$; p = percentage, e = difference between actual and predicted values of the outcome). It is used to assess accuracy or goodness-of-fit in forecasting (Anderson & McNeill, 1992; Makridakis *et al.*, 1998).

(Table 2 about here)

The best neural network for *worn-out* was one with 2 hidden layers of 14 nodes each, with predicted training accuracy 86.39%. The single predictor with relative importance RI ≥ .10 was age (RI = .11). Manager demands, tenure, number of breaks taken, gender, social support, home-work support, communication with manager, equipment suitability and job security were also salient for the worn-out model (.10 > RI ≥ .05). The predicted values for worn-out corresponded well to the actual values (r = .51) and explained 26.01% of variance in worn-out. The best network for *job satisfaction* was one with 2 hidden layers of 9 nodes each and predicted accuracy 85.14%. The most salient (RI > .10) predictors of job satisfaction were: communication with manager (RI = .18), relationships with colleagues (RI = .15), teamwork (RI = .13), age (RI = .12), decision latitude (RI = .12), job security (RI = .12), time for training (RI = .11) and social support (RI = .11). Nine additional inputs were also included in the network (.10 > RI ≥ .05). The correlation between estimated and actual values was r = .61 and the network explained 37.21% of variance in job satisfaction scores.

Multiple Linear Regression Analyses

Two statistical (stepwise) multiple linear regression analyses were performed for worn-out and job satisfaction with the employee variables (gender, age, tenure and social support; Step 1) and the work characteristics (Step 2) as predictors, using SPSS Regression. This was chosen because (a) there was no theory to guide the models and (b) this strategy to variable selection is similar to the neural networks procedure where variables are allocated a random weight which is adjusted through iterations as training proceeds and represents a combination of the forward and backward deletion procedures in statistical regression. Hierarchical regression was used within steps. The cases-to-IVs ratio for the analyses was generous, with $N = 1003$ fulfilling the minimum of $N = 50 + 8m$ (m = number of predictors). None of the bivariate correlations between predictors were > .90, indicating no multicollinearity. Evaluation of normality led to the logarithmic transformation of age to reduce skewness. Bivariate correlations between predictors and outcomes revealed weak to medium relationships. The ranges of r between .06 and .27 ($\bar{r}$ = .15) for worn-out and between .09 and .37 ($\bar{r}$ = .19) for job satisfaction were within those reported in meta-analytic studies (e.g., $\bar{r}$ = .30, R^2 = .09 for job satisfaction, Viswesvaran, Sanchez, & Fisher, 1999). Table 3 shows the predictors included in the regression models, variance explained (R^2), F values, unstandardized regression coefficients (B) and intercept, standardized regression coefficients (β) and t values for the final models. Some missing data resulted in $N = 962$ which is adequate for an effect size $f^2 = 0.02$ (equivalent to $R^2 = 0.02$; $p = .05$, 18 predictors) and statistical power of .80 (Cohen, 1988).

(Table 3 about here)

R for regression on *worn-out* was significantly different from zero, $F(8, 953) = 24.03$, $p < .01$. Gender (β = .19, $t = 6.10$, p < .01) and social support (β = -.12, $t = -3.84$, $p < .01$) contributed 6.79% in shared variance of worn-out scores. The work characteristics that contributed significantly to worn-out were manager demands (β = -.11, $t = -3.43$, $p < .01$), number of breaks taken (β = -.11, $t = -3.43$, $p < .01$), equipment suitability (β = -.07, $t = -2.35$, $p < .05$), time for training (β = -.06, $t = -1.96$, $p < .05$), job security (β = -.08, $t = -2.36$, $p < .05$) and others' knowledge about one's job (β = -.06, $t = -2.00$, $p < .05$) and contributed another 9.99% for a total of 16.78% (adj. $R^2 = .16$) in explained variance in worn-out scores. The model for *job satisfaction* was also significant, $F(8, 953) = 44.24$, $p < .01$. The job characteristics decision latitude (β = .19, $t = 5.72$, $p < .01$), communication with manager (β =

.18, $t = 5.54$, $p < .01$), initial training ($\beta = .12$, $t = 4.22$, $p < .01$), equipment suitability ($\beta = .10$, $t = 3.22$, $p < .01$), manager demands ($\beta = .08$, $t = 2.75$, $p < .01$), job security ($\beta = .09$, $t = 3.22$, $p < .01$) and teamwork ($\beta = .11$, $t = 3.16$, $p < .01$) contributed 24.55% in shared variance in job satisfaction scores. Altogether, 27.08% (adj. $R^2 = .26$) of job satisfaction was explained.

Comparing Performance

It is often difficult to find metrics on which the performance of two different techniques can be compared, since different fit indices apply to different approaches. Here, performance comparisons were made on the basis of correlations between actual and predicted values (validation sets) and effect sizes for both approaches. To achieve this, the regression equations $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n$ were solved. Missing values in the regression inputs created missing values in the predicted variables and therefore a small number of cases were deleted from subsequent analyses. Incurred data loss was between 1.69% (job satisfaction) and 2.59% (worn-out). Table 4 presents the performance evaluation indices, including correlations (r) between actual and predicted values, Fisher z (a test of difference between two independent correlations, Bruning & Kintz, 1977), variance explained (R^2), means for observed (M_{act}) and predicted (M_{pred}) values with their standard deviations (*SD*), mean squared error (MSE), mean absolute percentage error (MAPE) and percentage change (%Δ) in fit indices.

These results indicate that the neural networks outperformed the linear regression models. The correlations between actual and predicted values were significantly higher for both the worn-out (Fisher z = -2.22, $p < .05$) and job satisfaction (Fisher z = -2.00, $p < .05$) networks vis-à-vis their linear regression equivalents. The neural networks explained 9.20% ($R^2 = .09$) more variance in worn-out scores (with an improvement of 1:55 or 54.73% over the linear regression model) and 10.20% ($R^2 = .10$) more variance of job satisfaction scores (a ratio of 1:1.38 or 37.61%). MSE of the best linear regression models were higher than those of the best neural network (9.73% and 12.00% for worn-out and job satisfaction, respectively). MAPE was lower for the neural networks by 11% for both worn-out and job satisfaction.

(Table 4 about here)

Model Architecture

The relative positioning of the predictors in the models was also examined. The qualitative comparisons between the regression models and neural networks indicated some agreements and disagreements. Specifically, both the neural networks and regression models assigned highest priority to manager demands (the most salient predictor), number of breaks taken, equipment suitability, and job security as the most salient work characteristics and determinants of worn-out. However, the regression analysis also included time for training and others' knowledge of work, whereas the neural networks included home-work support, communication with manager, and job security in the models.

Similarly, both neural network and regression model of job satisfaction included decision latitude, communication with manager, initial training, equipment suitability, manager demands, job security, and teamwork as salient predictors. However, the neural network included six additional work characteristics, which the linear approach did not deem important: relationships with colleagues, time for training, home-work support, facilities, others' knowledge, and number of breaks taken.

Furthermore, positioning of the salient work and organizational characteristics was different in the two approaches. For example, both neural networks and linear regression placed communication with manager high on the list of salient work characteristics for job satisfaction. However, decision latitude, initial training, and equipment suitability were much lower in the relative rankings of the neural networks than in the regression models. Teamwork and job security, on the other hand, were both higher on the list.

Discussion

The focus of the present study was to establish whether artificial neural networks would provide better fit than the traditional multiple linear regression analysis in modeling the relationship between work characteristics and work-related health. It was expected that there would be differences in (a) variance explained between the linear regression models and the neural networks, and (b) the relative positioning of the predictors in the architecture of the models. The results fulfilled these expectations: comparisons indicated improvements of the networks over the regression models and, most importantly, differing model architectures. By additionally demonstrating that underlying assumptions are an important consideration in choosing analytical techniques, the study can help to refine current practice. Neural networks provide a contender approach to examining the relationships between work and health and may prove helpful in improving decision-making concerning job design and risk management.

Model fit was examined from two different perspectives: one that focuses on fit indices (error measures, variance explained) and one that examines model architecture (predictors included in the models and relative positioning). All performance indices favored the neural networks, with significant differences in the linear-to-nonlinear correlations. The nonlinear approach explained more variance in scores than the linear models ($R^2 = .26$ for worn-out and $R^2 = .37$ for job satisfaction). The ratios of 1.53 and 1.37 for the linear-to-nonlinear differences in variance explained are not large deviations from the average 2.10 reported by Guastello (2002). It should be noted that perfect performance indices are often neither attainable nor necessarily desirable, as they may indicate overfitting of the model to the data. Unless the population is finite, perfect performance metrics do not necessarily imply 'good' modeling and prediction (Makridakis *et al.*, 1998). Although accurate prediction is difficult due to high levels of error in social issues (Frese & Zapf, 1988), nonlinear methods can potentially account for higher proportions of unobserved effect in complex nonlinear phenomena.

The present findings corroborate the empirical work on curvilinear effects of work characteristics on employee health outcomes. There is evidence for quadratic effects on job satisfaction of job demands (R^2 = .45, Warr, 1990), skill discretion (R^2 = .07, ΔR^2 = .01, Fletcher & Jones, 1993), social support (R^2 = .17, de Jonge & Schaufeli, 1998), job tension (ΔR^2 = .23, Zivnuska *et al.*, 2002), decision latitude and social support (ΔR^2 = .003 to .006, Rydstedt, Ferrie, & Head, 2006). This evidence has been inconsistent (e.g., Muse *et al.*, 2003). For example, Jeurissen and Nyklíček (2001) did not find any significant relationships between job demands/job autonomy and job satisfaction. Similarly, Warr (1990) did not find support for nonlinear effects of decision latitude on job satisfaction. In terms of curvilinear effects of work characteristics on worn-out, there is some evidence for curvilinearity between emotional exhaustion and job autonomy (R^2 = .28, de Jonge & Schaufeli, 1998), inequity (quadratic, van Dierendonck, Schaufeli, & Buunk, 2001), and time pressure (R^2 = .55 to .73, Teuchmann, Totterdell, & Parker, 1999). Although the empirical evidence does not shed much light on the shape of the relationships, the evidence for the existence of nonlinear relationships is plentiful. Such inconsistent findings may be due to the predominance of linear regression techniques such as polynomial regression, an inherently linear approach (Karanika, 2006), and the fact that the majority of cited empirical work has focused mainly on bivariate relationships. As Schneider (1987) notes, examination of one particular element of the system provides little information about the whole network.

Beyond performance metrics, differing model architectures were also revealed. The neural networks diverged from the linear regression models in both the number of salient predictors and the relative importance of these predictors for worn-out and job satisfaction. Allowing for complexity and nonlinearity produced a job satisfaction network with twice as many predictors and better predictive capacity than the linear model. Relationships between work characteristics and well-being and also among work characteristics as predictors of health outcomes may be more complicated than traditional linear approaches can accommodate.

Decisions on job design and management clearly depend on the accurate assessment of potential risks to employee health. Risk assessment typically relies on probabilistic risk analysis (Clarke & Cooper, 2004; Glendon, Clarke, & McKenna, 2006) which uses linear methods. Evidently, a risk assessment for work-related health that uses a linear approach might fail to acknowledge the impact of a range of important work characteristics, and examining bivariate relationships between hazards and outcomes is less informative for practice than a concurrent examination of a range of hazards (Karanika-Murray *et al.*, *under review*). To the extent that psychosocial phenomena are complex and nonlinear, nonlinear approaches conform to best practice in decision-making for the management of health at work.

By enabling a range of variables to participate in many different representations, neural networks do not impose a priori relationships on the data but allow to learn from those data. Despite being a 'black box' application (Paruelo & Tomasel, 1997), neural networks can minimize some types of measurement error. Further, multicollinearity and non-normal distribution of predictors do not affect the networks, complex nonlinear relationships can be accommodated, and otherwise misrepresented variables can be included in the models. Moreover, they have the potential to integrate internal processes (e.g., learning, emotions) with higher systemic external representations (e.g. social relationships, behavior) (see Lowe *et al.*, 2003). Ways to 'open the black box' include, for example, examination of weights and confidence intervals, use of graphical methods, estimation criteria, and diagnostics (e.g., Price *et al.*, 2000; Sale, 1994). These are not readily applicable yet, but "methodology and statistics are computer-dependent enterprises […] as computer technology advances, the ability of researchers to advance the field increases dramatically" (Shadish, 2002, p. 12).

As mentioned, perfect performance indices would indicate overfitting of the models to the data, which would have implications for the generalizability of the findings. In the present study, generalizability is tenable in two ways: (i) by not being overfitted, the models are flexible enough to accommodate small changes and generalize to new data (e.g., DeTienne *et al.*, 2003; Makridakis *et al.*, 1998), and (ii) the original studies were carried out in range of organizations which covered a variety of job roles. In total, they represent large organizations in the private sector (see Cox *et al.*, 2000). Although it was not possible to compile a list of the range of jobs represented, these included knowledge employees, manual workers, customer services staff, managerial and administrative staff, etc. A homogeneous high risk occupational sample might have yielded higher performance indices, since "nonlinearity is expected to be more pronounced in studies among jobs that produce extreme scores on job characteristics" (de Jonge & Schaufeli, 1998, p. 391). Nevertheless, the sample's heterogeneity means that the results are generalizable across different groups.

Naturally, the use of a particular technique depends on the aims of the analyses. The most essential pieces of information for risk management are the accuracy of the overall model and the relative impact of specific work characteristics (potential hazards) on health. In such cases, neural networks provide an ideal tool. Although they are not ideal for discerning specific predictor-outcome relationships, they can also overcome some problems of commonly used techniques. Statistical approaches can be better when the aim is to examine the exact impact of a particular work characteristic. Sarle (1994) remarks that "statistical methodology is directly applicable to neural networks in a variety of ways" and that "better communication between the fields of statistics and neural networks would benefit both" (p. 11).

Neural networks and statistics can be used in harmony. For example, a stepwise approach to risk assessment can be adopted which will initially use neural networks to examine the impact of a range of work characteristics on health outcomes and to prioitize actions to reduce the most harmful ones. Multiple regression analysis can then be used to supplement this information by discerning the relationship between specific work characteristics and health outcomes (e.g., the partial derivatives approach for risk estimation in a multivariate curvilinear context, Karanika-Murray *et al.*, *under review*). A range of other approaches, such as principal components, discriminant, or cluster analysis, can also be used to examine neural network structure (Price *et al.*, 2000). As Sargent (2001) remarks, "neither method achieves the desired performance [but] both methods should continue to be used and explored in a complementary manner" (p. 1636). Although nonlinear researchers are required to compete with a long-standing expertise in linear statistics (Gilbert & Troitzsch, 2005), fruitful investigations reinforce the position that persisting in the development of the approach is worthwhile.

A range of methods for the study of nonlinear systems have been developed (Barton, 1994; Eidelson, 1997; Somers, 2001). For example, cellular automata (e.g., Nowak & Vallacher, 1998) have been used to model interactions among elements of a system over time (e.g., members of a family, voting behavior), multilevel simulation has been used to model attitude formation (e.g. Gilbert & Troitzsch, 2005), differential equations have been used to examine the relationships between positivity and flourishing (e.g., Fredrickson & Losada, 2005), and exponential (nonlinear) regression has been used to model motivational flow and leadership emergence (e.g. Guastello, 2002). Although specialized software is available (e.g., Gilbert & Troitzsch, 2005), choice of approach depends on the aims of the study, indicating that creativity in using available tools for new research agendas is important.

Limitations and Future Directions

Although steps were taken to maximize the ability of the networks to provide accurate models, points for caution ought to be raised, as with any new approach in an established area. Variance explained in outcome scores were no higher than 37%. As a general rule, low R^2 can indicate incomplete underlying theory or high measurement error in the data. Any type of analysis is as good as the data against which the conceptual models are examined (e.g., Price *et al.*, 2000). Inclusion of additional predictors in future studies could further improve the models. Future research could also compare these approaches using simulation data, normally distributed and with no missing values. Additionally, it is possible that unaccounted variance in the models is attributable to non-static elements. It was not feasible in the present study to address the dynamic aspect in the relationships between work and health, but neural networks can flexibly accommodate time-series data and such a truly nonlinear approach is prescribed for future work. The data were self-reported and cross-sectional. Biases associated with such data include: the influence of unmeasured third variables and individual differences, common method variance and the fact that it is impossible to ascertain the direction of causality from such designs (Zapf, Dormann, & Frese, 1996) and potential inflation of explained variance in outcomes. Any error was systematic and thus of no impact for the aims of the present study. Finally, it is important for future work to delineate the conditions under which neural networks outperform conventional approaches. This could include varying the types of nonlinearity and the percentage error in a dataset (Bansal *et al.*, 1993, found that linear regression were better overall in forecasting financial risk but neural networks were better with less accurate data).

Conclusions

This study demonstrated the viability of neural networks for modeling the impact of work characteristics on employee health outcomes. Neural networks produced better performance metrics and different relative importance of predictors for outcomes in the models. Although theoretical notions of nonlinearity in the relationships between work and health have long existed, a supposition of linear forms still dominates the field. As mentioned, a better model of reality is one that does not constrain complex and potentially nonlinear data into linear representations. We acknowledge that linear approaches have been instrumental in the development of psychological theory, but we also believe that we should explore and use new developments where possible and appropriate. Ultimately, improved assessment and decision-making for job design and the management of work-related health can only rely on accurate models that reflect the nature of the data.

Authors' Note

The study is based on the secondary analysis of data collected during several different studies funded by the GB Health & Safety Executive under grants made to the second author. The views expressed here are the authors' and do not necessarily represent those of any other person or institution.

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Table 1

Means, Standard Deviations and Correlations for the Study Variables

	M (*SD*)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Gender	.45 (.50)																			
2. Age	37.06 (10.56)	-.06																		
3. Tenure	9.92 (8.55)	-.28**	.54**																	
4. Social support	2.77 (1.18)	-.10**	.13**	.09**																
5. Staffing	2.14 (.84)	-.12**	-.11**	.02	.04															
6. Time for training	2.24 (.77)	-.06	-.04	.02	.11**	.24**														
7. Initial training	2.30 (.81)	-.08*	.09**	.07*	.13**	.05	.37**													
8. Job security	2.43 (.89)	.32**	-.11**	-.18**	.01	.01	.14**	.03												
9. Teamwork	2.26 (.80)	-.16**	-.15**	.05	.15**	.30**	.35**	.16**	.00											
10. Others' knowledge of job	1.90 (.69)	-.09**	-.06	.04	.09**	.26**	.18**	.17**	-.07*	.31**										
11. Manager demands	2.21 (.74)	.00	.03	.03	.16**	.29**	.26**	.15**	.19**	.28**	.15**									
12. Relationships with colleagues	3.11 (.69)	.01	-.07*	.02	.02	.16**	.05	.10**	.08*	.17**	.12**	.09*								
13. Communication with manager	2.54 (.88)	-.15**	-.17**	.03	.07*	.31**	.27**	.11**	.01	.46**	.24**	.29**	.22**							
14. Number of breaks taken	2.36 (.87)	-.09**	-.02	.02	.11**	.23**	.13**	.04	.13**	.19**	.15**	.23**	.13**	.20**						
15. Facilities	2.52 (.88)	.13**	-.09**	-.16**	.01	.12**	.08*	-.02	.18**	.11**	.09**	.16**	.13**	.13**	.42**					
16. Home-work support	2.79 (.78)	.10**	-.01	-.08*	.05	.09**	.07*	.04	.03	.14**	.08*	.13**	.20**	.11**	.11**	.08*				
17. Decision latitude	2.24 (.83)	-.04	-.07*	.00	.10**	.24**	.32**	.04	.19**	.45**	.19**	.34**	.20**	.33**	.17**	.09**	.13**			
18. Equipment suitability	2.49 (.79)	.02	.07	.01	.06	.21**	.22**	.22**	.17**	.22**	.17**	.22**	.11**	.15**	.17**	.18**	.09**	.19**		
19. Worn-out	18.80 (8.53)	.19**	-.10**	-.05	-.20**	-.19**	-.18**	-.12**	-.08*	-.19**	-.17**	-.27**	-.08*	-.17**	-.22**	-.07*	-.10**	-.17**	-.16**	
20. Job satisfaction	2.22 (0.01)	-.04	-.03	.03	.17**	.22**	.26**	.20**	.15**	.36**	.19**	.29**	.15**	.37**	.20**	.07*	.11**	.36**	.25**	-.31**

Note. * $p \leq .05$; ** $p \leq .01$ (2-tailed); N=879 (listwise); Gender was coded as 0=male, 1=female; Gender M indicates proportional representation.

Table 2

Neural Network Modeling Results

	Worn-out		Job satisfaction
Predictors	RI	*Predictors*	RI
Age	.11	Communication with manger	.18
Manager demands	.09	Relationships with colleagues	.15
Tenure	.08	Teamwork	.13
Number of breaks taken	.07	Age	.12
Gender	.07	Decision latitude	.12
Social support	.07	Job security	.12
Home-work support	.07	Time for training	.11
Communication with manager	.06	Social support	.11
Equipment suitability	.06	Manager demands	.10
Job security	.05	Tenure	.09
		Home-work support	.09
		Facilities	.09
		Equipment suitability	.08
		Initial training	.07
		Others' knowledge	.06
		Gender	.06
		Number of breaks taken	.06
Model	2 hidden layers (14 nodes each)		2 hidden layers (9 nodes each)
Predicted accuracy	86.39%		85.14%
r (observed vs. predicted)	.51**		.61**
R^2	.26		.37

Note. ** p ≤ .01 (2-tailed); *N* = 1003; RI = relative importance.

Table 3

Multiple Linear Regression Results

	Worn-out					
	Block 1			Block 2		
Predictors	B	β	t	B	β	t
(constant)	38.12		17.38**			
Gender	3.35	.19	6.10**			
Social support	-.85	-.12	-3.84**			
Manager demands				-2.01	-.17	-5.37**
Number of breaks taken				-1.08	-.11	-3.43**
Equipment suitability				-.81	-.07	-2.35*
Time for training				-.70	-.06	-1.96*
Job security				-.75	-.08	-2.36*
Others' knowledge				-.77	-.06	-2.00*
R^2	.07			.17		
ΔR^2				.10		
F	34.95**			24.03**		
*df*1, *df*2	2, 959			8, 953		
	Job satisfaction					
	Block 1			Block 2		
Predictors	B	β	t	B	β	t
(constant)	-.66		-2.97**			
Social support	.06	.07	2.65**			
Decision latitude				.23	.19	5.72**
Communication with manager				.21	.18	5.54**
Initial training				.15	.12	4.22**
Equipment suitability				.12	.10	3.22**
Manager demands				.12	.08	2.75**
Job security				.11	.09	3.22**
Teamwork				.14	.11	3.16**
R^2	.03			.27		
ΔR^2				.25		
F	24.90**			44.24**		
*df*1, *df*2	1, 960			8, 953		

Note. * $p \leq .05$; ** $p \leq .01$ (2-tailed); $N = 962$; Only predictors retained in the analyses are reported.

Table 4

Multiple Linear Regression and Neural Network Accuracy Comparisons

	r	Fisher z (n_{ANN}, n_{MLR})	R^2	ΔR^2	$\%\Delta R^2$	M_{act} (SD)	M_{pred} (SD)	MSE	%ΔMSE	MAPE	ΔMAPE	%ΔMAPE
Worn-out												
ANN	.51**	-2.21* (1003, 962)	.26	.09	54.73	19.77 (8.67)	19.04 (4.15)	56.29	9.73	61.33	8.09	11.65
MLR	.41**		.17			19.76 (8.66)	19.73 (3.55)	62.36		69.42		
Job satisfaction												
ANN	.61**	-2.00* (1003, 962)	.37	.10	37.61	3.21 (1.02)	3.15 (.63)	.66	12.00	26.14	3.35	11.36
MLR	.52**		.27			3.22 (1.02)	3.22 (.53)	.75		29.49		

Note. * $p \leq .05$, ** $p \leq .01$ (2-tailed); ANN = artificial neural networks; MLR = multiple linear regression; r = correlation between the actual and predicted values of the outcome variable; M_{act}, M_{pred} = means for actual and predicted values, respectively; MSE = mean squared error; MAPE = mean absolute percentage error; $\%\Delta R^2$, %ΔMAE, %ΔMSE and %ΔMAPE = percentage change relative to the best model.

Figure Caption

Figure 1. Feedforward multilayer neural network with 12 inputs, one hidden layer of 6 nodes, and one output.