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Modelling Team Cohesion during Military Conscription: a Multidimensional Model for Task Cohesion

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Abstract

This research aims to predict conscripts' task cohesion in groups using artificial neural network modelling (NNM). The prediction of task cohesion during military conscription lies on two domains of research. The first is related to team cohesion, its deconstruction, and its measurement, while the second is allied to nonlinear modelling in group behaviour research. To predict this multidimensional and complex phenomenon, the multilayer perceptron (MLP) and the radial basis function (RBF) neural networks are used. As a result, the team cohesion in conscript groups, which is a key variable in conscription service effectiveness, was predicted with high accuracy (MPL MOD2= 88% and RBF MOD8=90%) by the models created. The performed modeling shows that according to MPL MOD2 norm cohesion has 100% of normalized importance, while according to RBF MOD8, interpersonal cohesion is the best predictor (normalized importance=100%) for task cohesion in groups during conscription service.

Keywords: Multi-Layer Perceptron Neural Network; Radial Basis Function Neural Network; back-propagation algorithm; team cohesion; conscripts

1. Introduction

Task cohesion is one of the most powerful drivers that determines the team's determination to achieve the set goal together. At the same time, it is one of the most important factors in war, as it defines the combativeness and unity of small military units. Task cohesion is of special importance during compulsory military conscription, as it represents not only the transformation of a civilian into a new soldier, but also a "willingness to solve problems together in the process of achieving group goals" (Jue et al., 2020).

Although there is an increasing agreement that task cohesion is a key variable in conscription service effectiveness, there is a lack of proper measures that could be applied at the beginning of conscription service to predict a conscript unit's effectiveness. Task cohesion in conscript units is a multidimensional phenomenon that must be measured and modeled using nonlinear methods. Mathematically, artificial neural network (ANN) modelling is used for this purpose. The neural networks are able to handle large and complex systems with many interrelated parameters. The new evolutionary-based algorithm can be developed by simultaneously change the topology and the connection weights of ANNs by means of different combinations of genetic algorithm according expert's effort.

The main purpose of the present paper is to model task cohesion in conscript squads using an ANN-based prediction model. As task cohesion is a multidimensional and complex phenomenon that needs to be predicted at the beginning of the service to reach the maximum effectiveness of conscription service, we developed a simple prediction model using artificial neural networks. This model is based on pretested simple measurements of other group cohesion factors, individual factors, and/or leadership factors. All together, these straightforward measurements represent decisive factors for task leadership.

The neural network approach could be helpful for highlighting these decisive factors that could be easily adjusted already during the first weeks of conscription service without waiting until the level of task cohesion becomes measurable. Accordingly, ANN modelling was carried out *aiming* to build a conscript squad effectiveness prediction model based on squads' task cohesion.

The paper proceeds as follows. First, we highlight an existing research gap on task cohesion in the military as well as opportunities to use ANN modelling to fill it. We continue by outlining our research instruments and measurement models. The main findings of preliminary analysis and parameter description for the ANN training and testing are followed by a demonstration of the case processing results. At the end of the article, we discuss the main implications for theory and practice and provide suggestions for future research.

2. State –of–the – art

Modelling task cohesion during military conscription lies on two domains of research. The first is related to team cohesion, its deconstruction, and its measurement, while the second is allied to nonlinear modelling in group behavior research. We continue by briefly discussing these two domains and highlighting the gap that need additional research.

In military terminology, the phenomenon of task cohesion is named and measured differently. On the one hand, task cohesion is perceived as well to fight; it is defined as a soldier state of mind which affects a soldier's commitment to the mission (Rielly, 2000). On the other hand, this is referred to as esprit de corps, i.e., an honor to share a common goal in a unit, shared enthusiasm and dedication(Sledge, 2007). However, it is not possible to rely on military terminology only to analyze this phenomenon as, according to the RAND report, there is no clear answer or central point of reference to explain this phenomenon and allow it to be assessed. In organizational behavioral theory, this phenomenon is defined by one term - task cohesion. Task cohesion is an organizational construct with a wide developed theoretical background. Thus, to measure and model synergistic human will in the military, we have to employ the concept of cohesion which is the most important group variable. It should also be noted that task cohesion is already operationalized in the theoretical and empirical literature by highlighting role of shared understanding, communication and personal ambiguity(Petersen et al., 2019); task cohesion as well impacts on team performance (van Vianen & de Dreu, 2001) and burnout (Al-Yaaribi & Kavussanu, 2017).

Based on previous research on organizational behavior, it has been found that teams are dominated by nonlinear feedback networks (Losada & Heaphy, 2004); team members are constantly involved in the ongoing positive and negative feedback. These relationships can only be understood using nonlinear models that are able to capture the complex dynamics inherent in these interactional processes. Mathematically, artificial neural network (ANN) modelling is used for this purpose. ANN modelling is a precise method for human behavior research; its application ranges from organizational citizenship (Zorlu & Bastemur, 2014) to workplace withdrawal (Abubakar et al., 2017), result prediction. The ANN approach has been used to analyze and predict different military challenges and solutions, for example, the level of stress during conscription (Bekesiene et al., 2021) and results of virtual military training (Şuşnea, 2010) as well as for serious games for live training (Reed et al., 2019); methodological discussion how to apply ANN to improving groups chosen for military purposes is discussed is discussed in earlier studies (Menke & Martinez, 2008).

Artificial neural networks have one additional advantage in predicting task cohesion. It is the ability to find pathways underlying a complex set of data and to discover a hidden association between different factors. Hence, according to (Thomas et al., 2016), an artificial neural network can investigate the complex associations between the level of dependent and independent variables.

Based on this literature review on the state-of-the-art we can conclude that this field has a wide developed theoretical background. Despite the significant progress in the field we also identified a research gap as there is no methodology to predict task cohesion in the nonlinear feedback groups. Taking into consideration that conscripts are constantly involved in the ongoing positive and negative feedback in their squads, we rise a research question of how to analyze, model, and predict task cohesion in conscript teams considering that teams are dominated by nonlinear feedback networks?

3. Materials and Methods

The analysis in the study was performed by employing the artificial neural network (ANN) modelling. For this purpose, neural network models (NNM) such as the multilayer perceptron (MLP) and the radial basis function (RBF) were built to predict the team cohesion in conscript squads. The analytical measurements of the designed models were assessed by comparing the result data, and for validation were used the two statistical values, the determination coefficient (R^2) and the mean square error (MSE) measure. There were constructed the MLP and RBF neural network models with one hidden layer. Reducing an error function helps to optimize the number of units in the hidden layers. For modelling analysis, the study dataset was divided into three portions: training, testing, and holdout, where the IBM SPSS 27v software was used for the NNM modelling. Eight independent continuous variables which correspond to team cohesion were used as inputs and one dependent continuous variable for output in the NNM. In our case to optimize the predictive model's construction, there were designed numerous MLP and RBF ANNs which included from 5 to 50 hidden nodes.

The hidden neurons were optimized and the NNM training was carried out. The NNM modelling validation was focused on the objective function that evaluates the sum of square errors and helped to identify the difference between the measured values for the task cohesion level in squads. In this case, the least squares metric was used for NNM training data part. The designed neural network was validated through statistical analysis, and there were compared NNM prediction values with the collected dataset.

The NNM modelling with hidden nodes greater than 50 were not continued due to the predictive capability decrease. The selection of the best NNM was accepted by considering the determination coefficient (R^2) and the mean square error which can be explained by the following equation:

$$MSE = \frac{1}{ns}\sum_{j=1}^{n}\sum_{i=1}^{s}\left(Y_{j,i} - y_{j,i}\right)^2, \qquad (1)$$

where $Y_{j,i}$ is the consummate value of the jth data sample at *the ith* data output and $y_{j,i}$ is the actual value of the jth data sample at *the ith* data output; n is the quantity of samples and s is the number of neurons at the output layer. The dissimilar mixtures of activation functions and neuron quantities were assessed by identifying the fitted model, considering the MSE.

3.1. Neural network modelling background

The multilayer perceptron network can be explained as a network of simple neurons named perceptrons. To explain the conception of MLP, one has to start from the explanation of one perceptron, and then to the possibility of computing a single output from multiple real-valued inputs by forming a linear combination according to its input weights and then possibly putting the output through some nonlinear activation function. Methodically, this can be explained by the following equation:

$$y = \varphi(\textstyle\sum_{i=1}^{n} w_i \cdot x_i + b) = \varphi(W^T \cdot X + b), \qquad (2)$$

where w represents the vector of weights, X is the vector of inputs, b is the bias and φ is the activation function. Figure 1 represents the signal-flow operation in the graphical view (Lei & Wu, 2007; Neruda & Kudová, 2005).

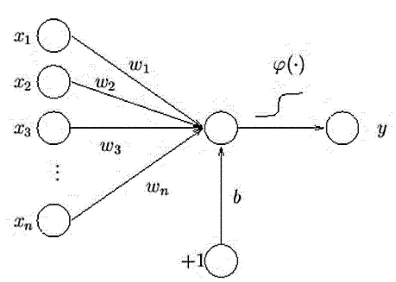

Figure 1. The perceptron signal-flow scheme.

The radial basis function neural network (RBFNN) is the most frequently used for NNM modelling (Hochreiter & Schmidhuber, 1999; Neruda & Kudová, 2005; Song et al., 1995; Sykora et al., 2020; Yang et al., 2013). The RBFNN characteristically includes three layers: the input layer, the hidden layer, and the output layer. The output layer produces a vector by a linear combination of the outputs of the hidden nodes to yield the final output (Neruda & Kudová, 2005; Sykora et al., 2020; Yang et al., 2013). The construction of n input and m output RBF neural network can be explained by the following equation:

$$y = f_j(k) = \textstyle\sum_{i=1}^{n} w_j^i\, \varphi_i(k), \quad for\ j = 1, \dots, m, \qquad (3)$$

where k = {k1, k2,...,kn} denotes the input vector for n inputs and y = {y1, y2,...,ym} represents the output vector for m outputs; w_j^i represents the weight of the ith hidden nodes and the jth output node and n is the total number of hidden nodes; $\varphi_i(\cdot)$ denotes the RBF of the ith hidden node. The linear combination of all hidden nodes presents the final output of the jth output node (k).

3.2. Sample and data collection

Eleven squads with totally 111 conscripts in the first months of service, when selected for this research. The data were collected in one battalion of the Lithuanian Armed Forces during the COVID-19 pandemic. This circumstance created a perfect environment for this research as an impact from the external environment was minimized in line with health safety guidelines. The average age of the participants was 20.3 years; the majority had secondary education (73.0%). Research was performed using self-reported questionnaire in the Lithuanian language.

3.3. Measures

Task cohesion in conscript squads was measured in the context of other group cohesion factors as well as in the context of leadership and individual factors of each conscript in a squad. Totally, three components were developed: group cohesion, leadership, and individual factors.

Group cohesion. Four types of group cohesion are measured using questionnaires: (1) task cohesion (CTS), (2) team cohesion (CTM), (3) interpersonal cohesion (CIP), and (4) norm cohesion (CNR). The most important for our study is task cohesion. It is measured using eight items (statements) that represent attitude towards esprit, de corps, and squad concentration on the tasks. The items of group cohesion are developed by adopting the Scale of Team Learning Behaviour in the Combined Joint Staff Exercise (CJSE) (Salo, 2008) and Group Cohesion Scale-Revised (Hedlund et al., 2015; Paananen et al., 2020). In total, group cohesion was measured using a list of 33 items.

Leadership. Two types of leadership are relevant for conscripts: platoon leadership (PLE) and squad leadership (SLE). Both variables are measured using a 4-item scale of exemplary leadership. Exemplary leadership in the military is a backbone especially in small group leadership (Jennings & Hannah, 2011).

Individual factors. Three individual factors were added to this research model: (1) attitude towards military service, (2) individual engagement, and (3) adjustment to a new physical environment. Personal attitude towards the military (ATM) is a strong factor during military conscription. According to (Ennouri et al., 2017), is a strong predictor of a strong commitment during conscription. In our study, we used 6-items from his scale on Commitment to Military Service. Individual engagement (IEN) in conscription and new roles was measured using the 9-item Utrecht Work Engagement Scale (UWES-9) (Balducci et al., 2010) modified for the military context. And finally, adjustment to a new physical environment (ADJ) was measured by a 7-item scale on adjustment to a new physical environment (ADJ).

To this end, this research model consists of one dependent variable (CTS) and eight independent variables. The variables and their description are shown in Table 1.

Table 1. Variables used in the study

Variable's code	Description of measurement
Group cohesion:	
CTS	Task Cohesion is an aggregation of eight items. All items are measured using Likert scale from 1–totally disagree to 7–totally agree; construct values vary in the interval [8–56].
CTM	Team Cohesion is an aggregation of twelve items. All items are measured using Likert scale from 1–totally disagree to 7–totally agree; construct values vary in the interval [12–84].
CIP	Interpersonal cohesion in the group is an aggregation of seven items. All items are measured using Likert scale from 1–totally disagree to 7–totally agree; construct values vary in the interval [7–49].
CNR	Norm Cohesion is an aggregation of six items. All items are measured using Likert scale from 1–totally disagree to 7–totally agree; construct values vary in the interval [6–42].
Leadership:	
SLE	Squad leadership is an aggregation of four items. All items are measured using Likert scale from 1–totally disagree to 7–totally agree; construct values vary in the interval [4–24].
PLE	Platoon leadership is an aggregation of four items. All items are measured using Likert scale from 1–totally disagree to 7–totally agree; construct values vary in the interval [4–24].
Individual factors:	
ATM	Attitude towards military service is an aggregation of six items. All items are measured using Likert scale from 1–totally disagree to 7–totally agree; construct values vary in the interval [6–42].
IEN	Individual engagement is an aggregation of six items. All items are measured using Likert scale from 1–totally disagree to 7–totally agree; construct values vary in the interval [9–54].
ADJ	Adjustment to a new physical environment is an aggregation of seven items. All items are measured using Likert scale from 1–totally disagree to 7–totally agree; construct values vary in the interval [7–49].

4. Results

This study was focused on developing models based on neural network performance when predicting team cohesion in conscript squads. The level of task cohesion was measured in eleven squads. After numerous NNM modelling, different MLP and RBF constructs were created and verified. This comprehensive modelling was completed to create an acceptable structure with an appropriate number of hidden layers and neurons. Since a higher number may cause overfitting, while a smaller number may not process the data adequately. These calculations were significant for designing team cohesion structure for the prediction models. The extensive modelling procedure allowed to control the optimum quantity of neurons, hidden layers and transfer functions.

Furthermore, there was the identified the model with the highest validation. The MLP and RBF models were used to compare the effect of different structures of the NNM on the output results. The comparative analysis helped to identify the best NNM, with the maximum coefficient of determination (R^2) and minimum training and testing MSE was chosen to predict the causes of team cohesion in conscript squads' levels.

4.1. Preliminary analysis results

Before data modelling, there was conducted the preliminary survey dataset analysis. The conducted descriptive statistics let to compare team cohesion in conscript squads by nine variables. The comparative graphical data analysis for eleven squads providing the mean rates of individual factors (ATM, IEN & ADJ), group cohesion (CTM, CTS, CNR & CIP), and leadership (SLE & PLE) identified after the conducted survey by self-reported questionnaire (see Figure 2). Following the NNM modelling rules, before NNM construction, first there was investigated the relationships between nine continue variables which were selected for data modelling. The main focus of this analysis was to identify how CTS, which was selected as a dependent variable, correlates with other chosen variables. Pearson's correlation coefficient was used to assess the correlations between the constructed variables. The investigations helped to recognize a significant correlation between the Task Cohesion construct (CTS) and the other eight variables at the 0.01 level (2-tailed) (see Table 2).

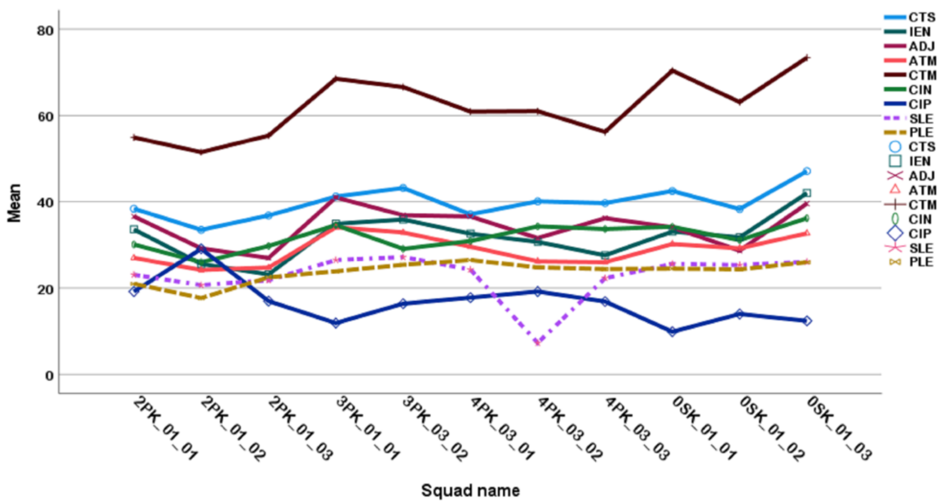

Figure 2. Comparison between the mean rates of individual factors (ATM, IEN & ADJ), group cohesion (CTM, CTS, CNR & CIP), and leadership (SLE & PLE) identified in the eleven squads' after survey dataset analysis.

Table 2. The relationship evaluation results between nine continue variables.

	CTS	IEN	ADJ	ATM	CTM	CNR	CIP	SLE	PLE
CTS	1.000	0.565**	0.443**	0.500**	0.714**	0.509**	-0.461**	0.268**	0.497**
IEN	0.565**	1.000	0.665**	0.643**	0.588**	0.436**	-0.401**	0.367**	0.435**
ADJ	0.443**	0.665**	1.000	0.520**	0.467**	0.486**	-0.369**	0.318**	0.361**
ATM	0.500**	0.643**	0.520**	1.000	0.596**	0.389**	-0.389**	0.405**	0.426**
CTM	0.714**	0.588**	0.467**	0.596**	1.000	0.574**	-0.505**	0.367**	0.479**
CNR	0.509**	0.436**	0.486**	0.389**	0.574**	1.000	-0.643**	0.184	0.346**
CIP	-0.461**	-0.401**	-0.369**	-0.389**	-0.505**	-0.643**	1.000	-0.308**	-0.418**
SLE	0.268**	0.367**	0.318**	0.405**	0.367**	0.184	-0.308**	1.000	0.397**
PLE	0.497**	0.435**	0.361**	0.426**	0.479**	0.346**	-0.418**	0.397**	1.000

Notes: **Pearson's rho correlation significance: **p<0.01 level (2-tailed).

The strongest statistically significant positive relationship was identified among the CTS and CTM ($r=0.714$, $p<0.001$). Moreover, a significant positive moderate correlation was observed between cohesion in performance (CTS) and individual engagement (IEN, $r=-0.565$, $p<0.001$), and between the attitude towards military service (ATM, $r=-0.500$, $p<0.001$),) and cohesion interpersonal result (CNR, $r=-0.509$, $p<0.001$). The significant negative correlation scores for CTS & CIP showed psychological (un)safety in the group variable ($r=-0.461$, $p<0.001$). Furthermore, significant positive high correlation coefficients were observed for: adjustment to a new physical environment (ADJ) and individual engagement (IEN) ($r=0.665$, $p<0.001$); engagement (IEN) and value of attitude towards military service (ATM) ($r=0.643$, $p<0.001$); the cohesion in team (CTM) and the individual engagement (IEN) ($r=0.588$, $p<0.001$). The calculation results of the relationships among nine variables are presented in Table 2.

4.2. Neural network modelling results

The artificial neural network modelling was applied to identify how task cohesion could be forecasted by eight independent variables: IEN, ADJ, ATM, CTM, CNR, CIP, SLE, and PLE, and how these variables separate task cohesion (dependent variable, CTS) and average ratings among the conscript squads.

The neural network modeling was conducted and the best structure with the lowest MSE was identified after repetitive modeling rounds using different specifications of activation functions and different proportions of training, testing, and holdout layers. Later, two neural network models were chosen with carefully optimized structures. These structures can be used for a precise representation of the prediction of the causativeness of team task cohesion. The best MLP MOD2 model for team task cohesion (CTS variable) can be described by subsequent parameters: first, the model's input layer included eight input variables; second, the NNM was constructed with one hidden layer and 20 neurons; third, one output layer with one output continuing variable (CTS – dependent variable) (see

Figure 3, green line).

In addition, the radial basis function neural network models were investigated and the RBF MOD8 was identified as one of the highest validated models, which can be used for CTS prediction. The RBF MOD8 was designed with training 40%, testing –40%, and holdout–20% of dataset partition; the Softmax function was used for hidden layer activation, and for the output layer – Identity function; 8 input neurons, 22 neurons in the hidden layer and 1 output. The red line in Figure 3 represents how RBF MOD8 predicts the changes in team task cohesion in eleven squads according to the measurements.

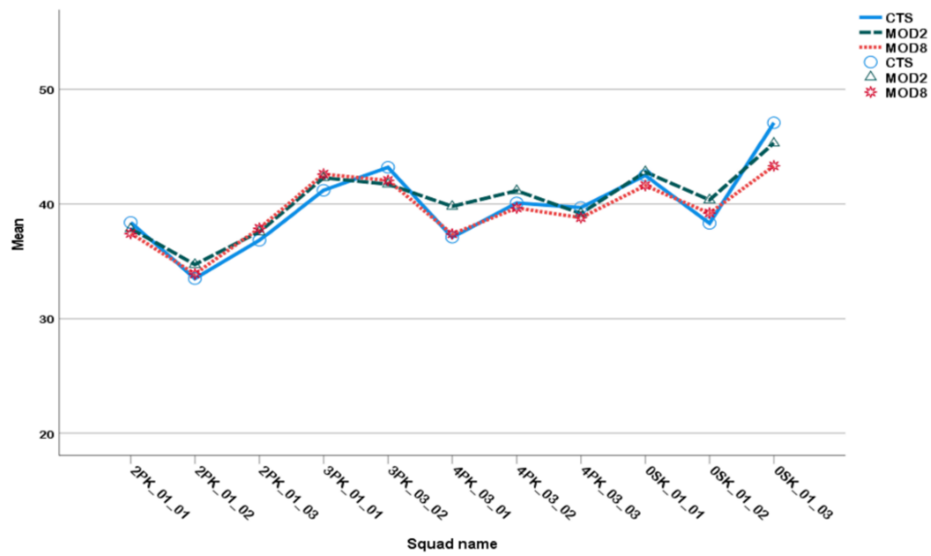

Figure 3. Comparison between survey data and predicted team task cohesion by NNM values: blue line—survey measurements of the changes in team task cohesion in eleven squads; red line—predicted team cohesion in eleven squads when using the RBF MOD8 with 4–4–2 of dataset partition, hidden layer activation function—Softmax, output layer – Identity function, 8 input neurons, 22 neurons in hidden layer and 1 output; green line—predicted team cohesion in eleven squads when using the MLP MOD2 with 4–4–2 of dataset partition, activation function—hyperbolic tangent, output layer – Identity function, 8 input neurons, 20 neurons in hidden layer and 1 output.

Table 3. The detailed information of MPL and RBF networks modeling.

Code	NNM	[1]NNEU	NNM Processing Summary			Hidden Layer(s)	Output Layer	[1]$MSE \times 10^{-2}$		[1]R^2
			Training	Testing	Holdout	Activation function	Activation function	Training	Testing	
MOD1	MLP	10	40%	40%	20%	Hyperbolic tangent	Identity	12.724	9.968	0.72
MOD2	MLP	20	40%	40%	20%	Hyperbolic tangent	Identity	4.139	10.914	0.88
MOD3	MLP	30	40%	40%	20%	Hyperbolic tangent	Identity	9.295	17.860	0.71
MOD4	MLP	10	30%	50%	20%	Sigmoid	Identity	9.090	8.490	0.75
MOD5	MLP	20	30%	50%	20%	Sigmoid	Identity	2.500	13.120	0.73
MOD6	MLP	30	30%	50%	20%	Sigmoid	Identity	3.817	18.562	0.73
MOD7	RBF	10	40%	40%	20%	Softmax	Identity	4.586	11.583	0.66
MOD8	RBF	22	40%	40%	20%	Softmax	Identity	3.717	8.229	0.90
MOD9	RBF	5	30%	50%	20%	Softmax	Identity	5.822	16.991	0.71
MOD10	RBF	20	30%	50%	20%	Softmax	Identity	1.287	15.338	0.76

[1]Notes: NNEU = number of neurons in the hidden layer; MSE = mean square error × 10^{-2}; R^2 = determination coefficient.

Table 4. Details of paired samples differences assessed by t-test.

Pair	Paired Differences					[4]Student's t-test		
	Mean	Std. Deviation	Std. Error Mean	95% Confidence interval of the Difference				
				Lower	Upper	t	df	p
[1] Pair 1 (CTS & MOD2)	-0.432	3.925	0.373	-1.170	0.306	-1.160	110	0.249
[2] Pair 2(CTS & MOD8)	-0.352	3.876	0.368	-1.081	0.377	-0.956	110	0.341
[3]Pair 3 (MOD2 & MOD8)	0.784	2.952	0.280	0.229	1.339	2.797	110	0.006

Notes: [1] Pair 1 survey results for team cohesion (CTS) and predicted by MLP–MOD2 (4–4–2 of dataset partition activation function—hyperbolic tangent, 8 input neurons, 20 neurons in hidden layer and 1 output); [2]Pair 2 survey results for team cohesion (CTS) and predicted by RBF–MOD8 (4–4–2 of dataset partition activation function—hyperbolic tangent, 8 input neurons, 22 neurons in hidden layer and 1 output); [3]Pair 3 judge the paired differences between the two dissimilar design models, MPL MOD2 and RBF MOD8.
[4]Student's t-test, df = degrees of freedom and p = Sig. (2-tailed).

The accuracy of the designed RBF MOD8 model was determined to be very good because of its capability to explain the variation of more than 90% of changes in the team task cohesion in the eleven groups; according to the small training and testing layer errors by MSE, these were training 3.717×10^{-2} and testing 8.229×10^{-2}. The comparison between survey data (blue line) and predicted team task cohesion by MLP MOD2 (green line) and RBF MOD8 (red line) values are shown in Figure 3.

4.3. Robustness of designed neural network model

To test the statistical difference between the team cohesion (CTS) measurements and two different construct, neural network models were conducted. The Student's t-test statistic for paired means evaluation was conducted between surveyed CTS values and predicted dataset by MLP MOD2 and RBF MOD8. Paired samples descriptive statistics for observed and predicted team cohesion are presented in Table 4. The Student's t-test demonstrates an insignificant average difference between CTS and those predicted by MLP MOD2 (t_{110} = -1.160, p = 0.249). Furthermore, the insignificant average difference is proved between CTS and RBF MOD8 (t_{110} = -0.954, p = 0.341). Moreover, the paired differences are observed between MLP MOD2 and RBF MOD8 (t_{110} = 2.792, p = 0.006). Furthermore, the conducted correlation analysis results show that the survey and predicted task cohesion by RBF MOD8 (r = 0.901, $p < 0.01$) and MLP MOD2 (r = 0.882, $p < 0.01$) were highly and positively correlated. The details of paired sample difference assessment by Student's t-test are presented in Table 4.

4.4. The importance of the independent variables

Neural network modelling provides an evaluation of the importance of eight independent variables: IEN, ADJ, ATM, CTM, CNR, CIP, SLE and PLE, in prediction of the CPE average rating in the squads. The IBM SPSS 27v software characterizes the normalized importance of the variables included in the NNM in a graphical view by a bar chart (on the top is presented variables of high importance, on the bottom – variables of low importance). In addition, the calculated values are presented in the table format.

Accordingly, Figure 4 and Figure 5 illustrate the results of normalized importance of variables for the MLP MOD 2 and RBF MOD8 neural networks' models that showed statistically significant high validation results by determination coefficient and MSE measures. Despite the fact that these two models are high validated, the importance of variables in CTS prediction are quite different. The MLP MOD2 identifies the three most important independent variables in the designed model; their importance is very close or equal to 100%: norm cohesion (CNR), team cohesion (CTM) and individual engagement (IEN) (see Figure 4). The most important variables in the RBF MOD8 model are interpersonal cohesion in the group (CIP), norm cohesion (CNR), and individual engagement (IEN) (see Figure 5).

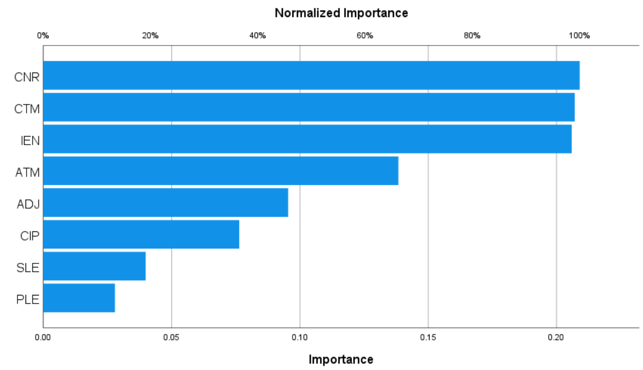

Figure 4. Normalized importance for model variables predicted by MOD2.

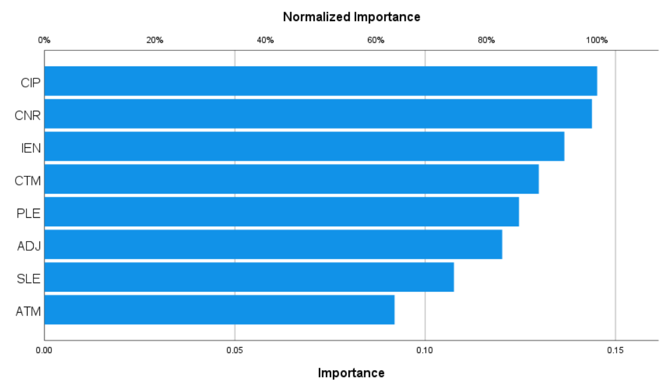

Figure 5. Normalized importance for model variables predicted by MOD8.

Additionally, detailed information about the predicted importance for all eight variables by MOD2 and MOD8 are presented in Table 5.

Table 5. Independent variable importance in the designed NNM.

Variables	MLP-MOD2 40%-40%-20%		RBF-MOD8 40%-40%-20%	
	Importance	Normalized Importance	Importance	Normalized Importance
IEN	0.206	98.5%	0.137	94.1%
ADJ	0.095	45.6%	0.120	82.8%
ATM	0.138	66.2%	0.092	63.3%
CTM	0.207	99.1%	0.130	89.4%
CNR	0.209	100.0%	0.144	99.1%
CIP	0.076	36.5%	0.145	100.0%
SLE	0.040	19.1%	0.108	74.1%
PLE	0.028	13.4%	0.125	85.9%

Source: authors' calculations.

The conducted neural network modeling analysis showed that norm cohesion reached the highest indication (CNR, normalized importance=100%) compared to the other seven predictors in MPL MOD2, while the interpersonal cohesion in the group (CIP, normalized importance=100%) was identified as the best predictors for task cohesion in the RBF MOD8 (see Table 5).

5. Discussion

This study was conducted to identify factors that best predict conscript squads‘ task cohesion already at the beginning of conscription service. Considering the nonlinearity of these factors, as they arise as a consequence of interpersonal and intrapersonal feedback in squads, the NNM application allowed to predict the level of task cohesion based on few variables. Most importantly, these variables could be observed (and measured) already at the beginning of conscription service, much earlier than task cohesion. Consequently, this study is important because it identifies these early warning factors that predict the desired outcome (task cohesion) with up to 100% normalized importance. In particular, the performed modeling shows that norm cohesion (MOD2 model) and interpersonal cohesion (MOD8 model) are the strongest predictors while modelling the level of task cohesion in squads during conscription service.

Mathematically, these results are gained after numerous NNM modelling and verifying different MLP and RBF constructs. This comprehensive modelling was completed to create an acceptable structure with an appropriate number of hidden layers and neurons. The modelling was performed considering the overfitting problem while exceeding an optimal ANN size (Caruana et al., 2001), as well as issue of data adequately while using too small number of data(Norgaard et al., 2000). These cautions were important in designing the team cohesion structure in the prediction models. Hence, this extensive modelling procedure allowed to control the optimum number of neurons, hidden layers, and transfer functions. The MLP and RBF models were validated. Following the mainstream practice (Baughman & Liu, 1995; Caruana et al., 2001; Ludermir et al., 2006) in ANN the best network model with the maximum coefficient of determination (R2) and minimum training and testing MSE was chosen for prediction.

The study findings go in line with the mainstream literature on small group research in the military where "military cohesion" is used as a general term to describe microlevel dynamics among soldiers that leads to combat efficiency (Käihkö, 2018). Based on the classical Truckman' group dynamics model (Bonebright, 2010a, 2010b; Tuckman & Jensen, 1977), the first stage of group formation is norming. Norm cohesion (in our study – CNR in MPL MOD2 model), which expresses a common tolerance in a group towards mistakes and otherness, creates a positive environment where an effective group can be formed. Together with this, our RBF MOD8 model predicts a high importance for interpersonal cohesion (in our study – CPI), as at the beginning of group formation people focus more on interpersonal relationships (Lambić et al., 2018).

The results of this study can have significant implications for designing and implementing the conscription services. Using these findings, responsible persons in the military units for conscript service could design conscription service programs in a way that at the beginning of the conscription service more emphasis would be placed on Individual engagement (IEN) and team cohesion (CTM) by highlighting norms in squads (CNR) or on interpersonal relationships (CIP) between group members.

6. Conclusions

In this study, neural network models (NNM) were designed using the multilayer perceptron (MLP) and the radial basis function (RBF). Created models predict team cohesion in conscript squads with high accuracy (MPL MOD2= 88% and RBF MOD8=90%). Our findings demonstrate that the highest accuracy is attained with a 4-4-2 partition. Using the multilayer perceptron (MLP) function, a model was developed that predicts task cohesion using norm cohesion (CNR, normalized importance=100%), team cohesion (CTM, normalized importance=99.1%) and individual engagement (IEN, normalized importance=98.5%). Very similar result was reached using the radial basis function (RBF) where interpersonal cohesion (CIP, normalized importance=100%) together with norm cohesion (CNR, normalized importance=99,1%) and individual engagement (IEN, normalized importance=94.1%) predicts task cohesion accurately. Both methods could be used interchangeably.

This research had several limitations. First, the application of self-report questionnaires for data collection could probably lead to personal bias and subjective perception. Further studies are needed to check if there are some differences in predicting task cohesion using observational or other less-bias data. Second, this study used only three types of variables that represent group cohesion, leadership, and individual factors. Future studies could include other elements of conscript military service.

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