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Linking Human Resource Management Practices and Firms' Performance Using Neural Networks:

Demonstration and Reporting

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ABSTRACT

This paper investigates relationship between human resource management practices (HRM) and performance. This paper demonstrates how analysis to reveal relationship among dependent and independent variables in HRM-performance link can be done using artificial neural networks (ANN). Statistical package for the social sciences (SPSS) was used to produce ANN. It argues that HRM research should utilize the breadth of statistics available including data science statistics. This study utilizes positivist paradigmatic stance, descripto-explanatory research design, and survey methodology. Questionnaires were used in data collection. The study found that HRM practices are important in predicting financial and non-financial performance. Synergetic relationship among HRM practices was also found to predict financial and non-financial performance of financial cooperatives in Kenya. Apart from exploring HRM independent variables, their interrelationships must be explored and reported in literature.

KEYWORDS

Artificial Neural Networks, Data Science, Financial Performance, Human Resource Management, Non-Financial Performance

INTRODUCTION

Data science or even artificial intelligence research in cooperatives is at infancy level. However, there are a couple of researches done. Like in other enterprises, cooperatives must aggressively adopt new technologies that will propel them towards stardom performance. Application of data science on cooperative data has been demonstrated by Elliot, Elliot & Sluis (2018) who researched on predictive analytics to demonstrate how membership heterogeneity affects sustainability of cooperatives. Chopras, Jiang, Toulis & Golab (2018) exhibited how data analytics can be used to improve cooperative education. Human resource management (HRM) field is beginning to turn attention towards data science so as to help organizations gain insights from voluminous data in their databases. Data science is a field that combines several fields-information technology, computer science, mathematics, operations research and statistics so as to generate knowledge from a pool of data for decision making and prediction. Applied in HRM it is referred to as Human Resource (HR) analytics. It uses big voluminous data that can be used for prediction. Weihs and Ickstadt (2018) notes data science is influenced by mathematics, statistics, computer science and operation research. Further, the authors

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note that roots of data science were firmly laid by Tukey's work on exploratory statistics as well as knowledge discovery in databases through data mining. Research studies on data science application within HRM field seems to be at infancy. This view is supported by Marler and Bondreau (2018) who note that adoption of HR analytics is slow and evidence from studies is limited. The authors further contents that HR analytics can be referred to as HR business intelligence, workforce analytics, people analytics and people research and analytics. Weihs and Ickstadt (2018) identify statistics for data science as descriptive statistics, predictive statistics and prescriptive statistics. Kremer (2018) proposes moderating variables in HR analytics such as data infrastructure, information technology and analytical skills by HR staff. Artificial neural network (ANN) has emerged as one of the potent tools in analyzing patterns that would not have been revealed before. There are a number of studies using ANN. Several studies have been done utilizing ANN in HRM (Khanjankhan, Askari, Rafiei, Perez-Campdesunar, De Miguel-Guzman Shaln, Hahemi & Shafii, 2017; Perez-Campdesunar, De-Miguel-Guzman, Sanchez-Rodriguez, Martinez-Viva, 2018; Somers, Birnbaum & Casal, 2018; Tung, Huang, Chen, & Shih, 2005; Wang & Shun, 2016). ANN analysis has a lot of value in HRM exclusively or in addition to regression models. Thus, this paper takes the view that ANN analysis and regression model analysis as data science techniques can complement each other. The paper also demonstrates output from ANN statistics and how to report them. Apart from formulating HRM variables to link with performance, and as a divergence from previous practice in selecting independent variables, the paper investigates synergetic relationship of HRM variables as an independent variable. Most studies on HRM and performance relationship (Dimba, 2008; Huselid, 1995; Khanjankan, Askari, Rafiei, Hasheni & Shafii 2017; Ngui, Mukulu & Gachunga, 2014; Spiliotis & Stavrou, 2007) focus on HRM practices but fail to deliberately study a key factor-the synergetic relationship among HRM practices and how it influences performance as dependent outcome and its multidimensional nature. The purpose of this paper was to investigate HRM performance link using ANN and demonstrate the relationship between HRM practices and performance. Additionally, the paper seeks to identify the most important variables that have the highest impact on financial cooperatives' performance from both financial and non-financial perspective. The paper develops a conceptual model that predicts performance of financial cooperatives as theorized to have two dimensions-financial and non-financial.

Research Objectives

This research is based on the following objectives:

1. To investigate the relationship between HRM practices and performance of financial cooperatives using ANN.
2. To demonstrate analysis and reporting using ANN in HRM-Performance research.
3. To identify the most important HRM predictors of financial cooperatives' performance using ANN.
4. To classify financial cooperatives using ANN based HRM practices and performance.

LITERATURE REVIEW

Literature covers researches done in HRM utilizing ANN. Perez-Campdesunar, De-Miguel-Guzman, Sanchez-Rodriguez, Martinez-Viva (2018) did a research on the factors that influence labor turnover using ANN. They established significant relationship between predictors such as school level and age and outcome variable of labor turnover. Additionally they established non-significant relationship between predictors-years of work, hierarchical position occupied in the organization and number of graduates and outcome variable of labor turnover. Somers, Birnbaum, Casal (2018) did a research using ANN to map and identify non linearities in wellbeing, supervisor support, control over work methods and employee wellbeing. They found that ANN explained significantly more variance than OLS in the variable wellbeing. They established a nonlinear relationship between supervisor support dimensions – trust and direct support and employee wellbeing. In addition Wang and Shun (2016) used back propagation and found out that work stress tolerance and cooperative ability as the most important factors in predicting labor turnover. Kaur and Fink (2017) proposed data science tools as R, Python, Cognos, Vizier, Innovisor, Tableau, Microsoft Excel, Stata, SPSS among others. They organized the tools in categories such as network analysis, cognitive computing and AI, text analysis, statistical analysis and business intelligence and analytics. Spiliotis and Stavrou (2007) used ANN and found significant relationship between HRM variables – training and communication practices, and organizational performance. In another study, Tung, Huang, Chen and shihi (2005) found that factors of work, and quality of work life predict job attributes of generation X employees. In addition, Khanjankan, Askari, Rafiei, Hasheni & Shafii (2017) used ANN to predict job performance of nurses. They concluded that agreeableness and reward as best predictors of job performance.

THEORETICAL AND CONCEPTUAL FRAMEWORK

Several models were used in generating variables to be used in the conceptual framework (Appelbaum, Bailey, Berg, & Kalleberg, 2000; Becker, Huselid, & Pickus, 1997; Guest, 1997; Purcell, Kinnie, Hutchitson, Rayton, & Swart, 2003). These models have dependent variables such as plant performance (Appelbaum et al., 2000), market value (Becker et al., 1997) financial performance (Guest, 1997), discretionally behavior and performance outcomes as dependent variables, with discretionally behavior being linked to performance outcomes (Purcell et al., 2003). The models architecture confirm that performance is a multidimensional concept. The lifecycle model proposed by Armstrong (2008) citing Baird and Meshoulam (1988) indicate that HRM effectiveness depends on its fit with stage of organization's development. They further argue that as organization grows, there is a tendency to formalize HRM in a department. This fact introduces two probable variables, presence of formal HR department and the size of the organizations in terms of membership or number of employees. The models identify several independent variables. Some used HRM practices such as selection, recruitment, appraisals, rewards, job design, involvement and security (Guest, 1997). Other HRM practices identified include job challenge/autonomy, training and development, career opportunity, job security, pay satisfaction, work life balance, recruitment and selection, team working, communication and involvement (Purcell et al., 2003). The resultant conceptual framework is contained in figure 9. Conceptual framework. There are several models and theories linking data science and HRM as used in previous studies. Notably, theoretical frameworks linking people analytics and performance are at a nascent stage and developing. This view is supported by Tursunbayeva and Di Lauro (2018) who argue that research on data analytics is at early stages. Additionally, Marler and Boudreau (2018) in a review on papers discussing data analytics in HRM demonstrated that theoretical domain of this area has many disciplinary roots. They identified return on investments in finance, technology acceptance model in information technology, theory of reasoned action in organizational behavior, resource based view (RBV) and competitive forces in strategic management. Competitive forces model supports this research since HR technology is one of the forces of change in HRM, and an enabler of competitive advantage. Technology acceptance model fits in this study since it explains why firms are either early adopters, late or no adopters of HRM technology. RBV explain that resources are a source of competitive advantage, and by extension HCA has to be viewed as a resource and a process that adds value in decision making within and beyond the HRM function. For creation of models and theories in data analytics, HRM researchers must first domicile this area in HRM under several terms that include but not limited to evidence based HRM as well as human capital analytics (HCA). Minbaeva (2017) calls for further research that links HCA and performance. With the dearth in models and theories in HCA research besides the generic ones, Minbaeva (2017) further developed a model that links firms' performance that seem to dovetail with current research. The model has four boxes. The first box has general business strategy, while the second box shows strategic business flowing from the first. Enhancing previous outcomes, the third box has three elements, namely data quality, analytical competence and strategic ability to act. Subsequently, the third and fourth box has organizational capability and business performance respectively. This paper utilizes ANN as HCA tool to demonstrate the HRM variables that financial cooperatives should focus on, thereby increasing their performance. Several theories support the link between HCA and performance, they include the intellectual capital, the human capital theory and the agency theory. Agency theory is one of the applicable theories in HCA since this theory can model employee behavior and make decision making towards firms performance better, thus increasing the synergy between principals and agents. Human capital theory in addition supports studies in HCA since HCA can be used as a tool that guides where investments can be done so as to give optimal returns to the organization. Finally intellectual capital theory has a lot of influence in the current research since it discusses how knowledge can be generated and stored in the organization. Amstrong (2008) defines intellectual capital as stocks and flows of knowledge available to the organization. HCA tools such as ANN can be used to analyze data in massive databases within the organization so as to gain new knowledge.

Rationale of the Study

This study contributes to the young but vibrant discourse on use of ANN in prediction of HRM phenomena. It gives directions and guidelines in reporting this kind of research. It contributes to the persistent questions surrounding HRM and performance link. The research fincings will be important for both HRM practitioners and researchers. The research is important for performance of financial cooperatives and argues that managers of these organizations should have capacity to use and deploy ANN in their prediction of variables within the organization.

METHODOLOGY

This research utilizes descripto-explanatory research design based on positivist philosophy. A questionnaire that used five point scale has been used. The study was done in Nairobi City County in Kenya. Nairobi City County was chosen because it provides a good mix of small, medium and large financial cooperatives. Drop and pickup questionnaires were highly quantitative with Likert matrix being adopted for every variable. Simple random variable was used to select a sample size of 340 financial cooperatives, arrived at using Cochran (1977) formula from a population of five thousands financial cooperatives. Variables were measured using five point Likert scale that enabled collection of ordinal data. Cronbach alpha was used to establish reliability while validity was established using Exploratory Factor Analysis (EFA) which generated the table of communalities, Kaiser-Meyer-Olkins (KMO) and Bartlett's test table. Reliability scores for all the variables were good as shown on figure 18. Reliability statistics with alpha values greater than 0.6. All tables showing KMO values for all the variables had adequate values in all cases (KMO > 0.6) as shown on figure 29. Performance management KMO and Bartlett's test, figure 31. Synergetic relationship KMO and Bartlett's test, figure 19. Financial performance KMO and Bartlett's test, figure 21. Non-financial performance KMO and Bartlett's test, figure 23. Resourcing practices KMO and Bartlett's test, Figure 25. Reward management KMO and Bartlett's test and figure 27. Training practices KMO and Bartlett's test. This indicated sample adequacy of variables. Bartlett's test was applied on all the variables as shown in figure 29. Performance management KMO and Bartlett's test, figure 31. Synergetic relationship KMO and Bartlett's test, figure 19. Financial performance KMO and Bartlett's test, figure 21. Non-financial performance KMO and Bartlett's test, figure 23. Resourcing practices KMO and Bartlett's test, figure 25. Reward management KMO and Bartlett's test and figure 27. Training practices KMO and Bartlett's test. In all the tables *p*-values were less than 0.05 indicating that correlation matrix was not an identity matrix. Figure 20. Financial performance communalities, Figure 22. Non-financial performance communalities, figure 24. Resourcing practices communalities, figure 26. Reward management practices communalities and figure 28. Training practices communalities, present communalities for all the variables. Items that had factor loadings of less than 0.4 were dropped from further analysis. SPSS software was used in analyzing data. The paper utilized ANN that uses multilayer perceptron architecture. Associated ANN tables and graphs such as Receiver Operating Characteristic Curves (ROC) were utilized. Seven covariates were entered in the input layer of ANN. Batch mode was used in training. ANN had one hidden layer and four outputs. It was designed using feed forward architecture. To analyze data using ANN the researcher used the following procedure: Analyze > Neural networks > multilayer perceptron. Under variables option select dependent and covariates. Under training option, select the mode of training the ANN. Lastly, under output check the checkboxes under network structure and network performance then click OK. The two dimensions of performance that is, financial and non-financial were transformed to binary from five point dimensions before use of ROC curves.

FINDINGS AND DISCUSSIONS

The resultant network diagram is shown in figure 1. Neural network diagram. As shown in figure 17. Variable importance, reward management, synergetic relationship among HRM practices, employee resourcing and training practices in that order were the most important variables in predicting financial and non-financial outcomes in financial cooperatives. The same information is depicted in graphical format in figure 4. Normalized importance. Figure 10. Network information table indicates the input layer covariates, the hidden layer and output layer independent variables. Figure 11. Model summary indicates average percent incorrect predictions of 19.6 percent in the training sample which indicates 80.4 correct predictions. Figure 12. Parameter estimates indicates parameters of predicted and estimated values for input and output layers. Grey lines in ANN indicate positive weights while blue lines indicate negative weights. Thickness of either line indicates the magnitude of each weight. Two ROC curves were produced for the two dependent variables. The curves are away from the diagonal line indicating tests for the two models are not worthless. The curves in the two ROCS closely follows left and top borders indicating acceptability of the model for classification. The ROCs are shown in figure 2. Financial ROC curve and figure 3. Non-financial ROC curve. Figure 16. Area under curve shows that the area under curves for financial variable (Area =0.875 > 0.5) and for non-financial variable (Area = 0.855 > 0.5) are excellent. Four variables were found to have elevated importance in predicting performance of financial cooperatives according to figure 17. Variable importance. These variables include employee resourcing practices (Normative importance = 100%), performance management (Normative importance = 84.9%), synergetic relationship of HRM practices (normative importance = 64.7) and reward management (Normative importance = 73.5). Predictive models were developed as shown in figure 13. Non-financial classification and figure 14. Financial Classification, for non-financial and financial dimensions of performance respectively. Overall accuracy for prediction as shown in figure 15 was 80.4. Figure 14. Financial Classification indicates that the model is a good classifier with 86 percent accuracy. From the low financial group, the model was able to classify 21 out of 36 as low financial with 58 percent accuracy. In the high financial group, the model was able to classify 92 out of 99 as high financial with accuracy of 92.9 percent. Non-financial classification is contained in figure 13. Non-financial classification. Within the low retention group, the model was able to classify 25 out 45 as low retention with accuracy of 55.6 percent while within the high retention group, the model classifies 79 out of 90 as high retention with accuracy of 87.8 percent. Overall accuracy for non-financial classification is 78.9 percent. Both figures 5. Non-financial gain chart and 6. Financial variable gain chart are gain charts which indicates effectiveness of the model in prediction. In figure 5. Non-financial gain chart, depicts differences before and after use of predictive model. The figure indicates positive gains when organizations use the model to predict non-financial performance. The gain for high retention at 10 percent is 1.5 while the gain for low retention is 2.7. In figure 6. Financial variable gain chart, the gain at 10 percent is 1.3 for high financial and 3.1 for low financial which are all greater than 1. The lift for non-financial variable as indicated in figure 7. Non-financial lift chart at 10 is 1.5 for high retention and 2.75 for low retention. From figure 8. Financial variable lift chart, the lift at 10 percent is 1.35 for high financial and 3.75 for low financial all indicating the model is better at prediction than random.

These results indicate that first, HCA tools can be successfully be applied on cooperatives data. With many cooperatives formalizing HRM in Kenya, there is a need to develop data science knowledge, skills and attitudes. While data science is a broad area of study, the adoption of the tools should match the size of organizations as well as other circumstances peculiar to the organization. The questions to be answered in data science research must match the business. The study has demonstrated that financial cooperatives must concentrate on both financial and non-financial dimensions of performance as they are equally important. HRM outcomes such as HRM effectiveness must form the basis for non-financial performance. Only then will performance of financial cooperatives be stable and sustainable. The results from this study are similar to those of Stavrou, Charalambous, & Spiliotis (2007) who found a relationship between training and performance, using ANN. Huselid (1995) also confirmed the positive relationship between training and performance. Dimba (2008) found a relationship between performance management practices and reward management practices on one hand and performance on the other, which is consistent with the current study. The findings are also similar to Ngui, Mukulu & Gachunga (2014) who found that resourcing practices have an influence on performance.

Figure 1. Neural network diagram

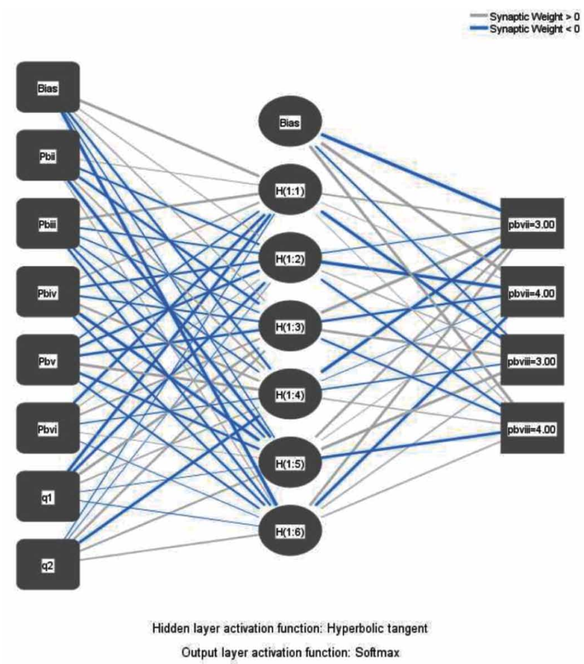

Figure 2. Financial ROC curve

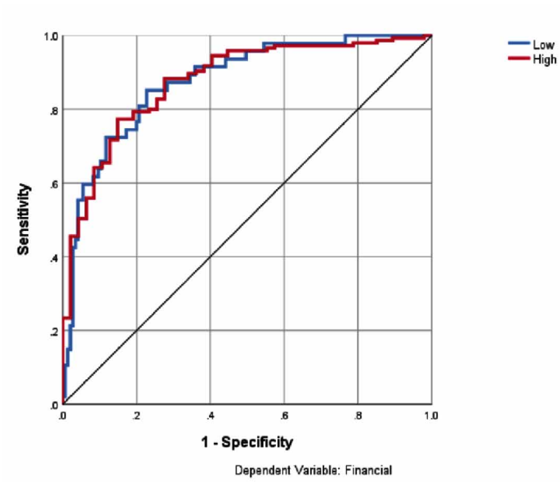

Figure 3. Non-Financial ROC curve

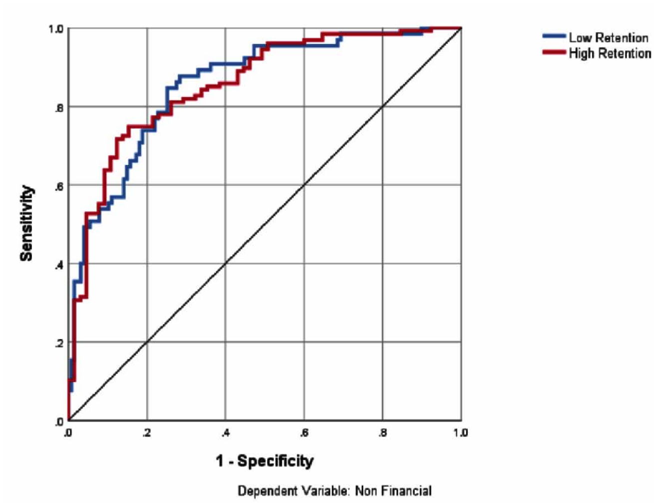

Figure 4. Normalized Importance

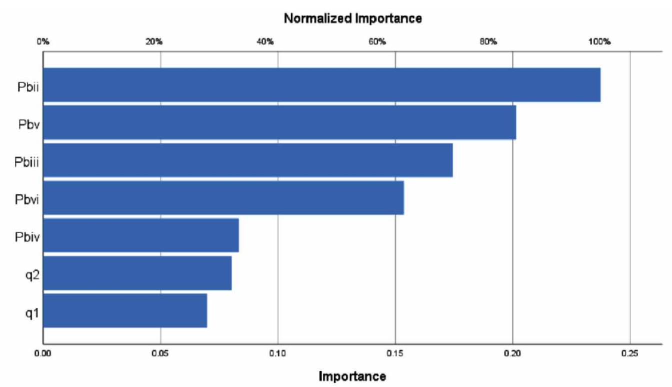

Figure 5. Non-financial gain chart

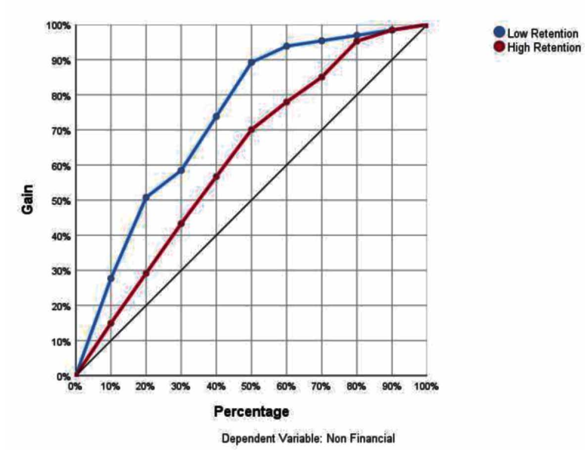

Figure 6. Financial variable gain chart

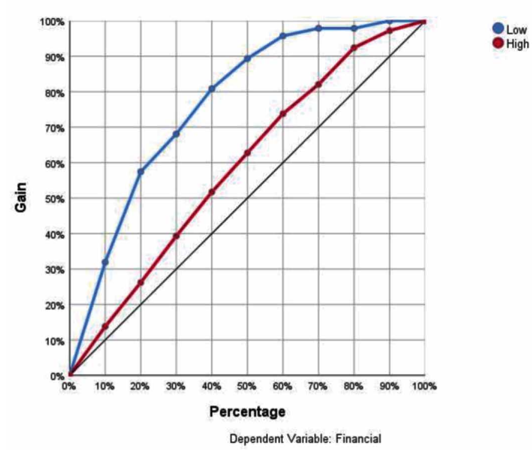

Figure 7. Non-financial lift chart

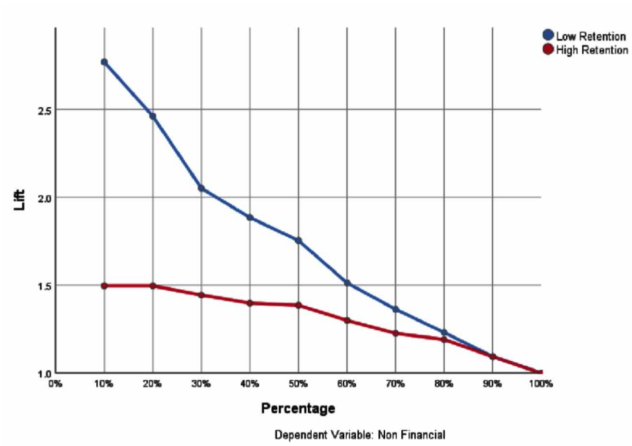

Figure 8. Financial variable lift chart

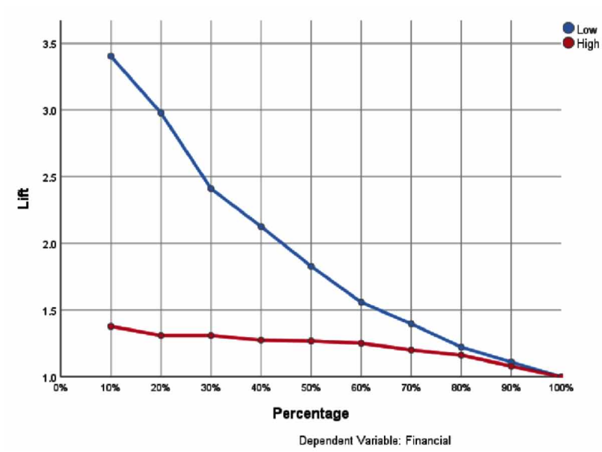

Figure 9. Conceptual framework

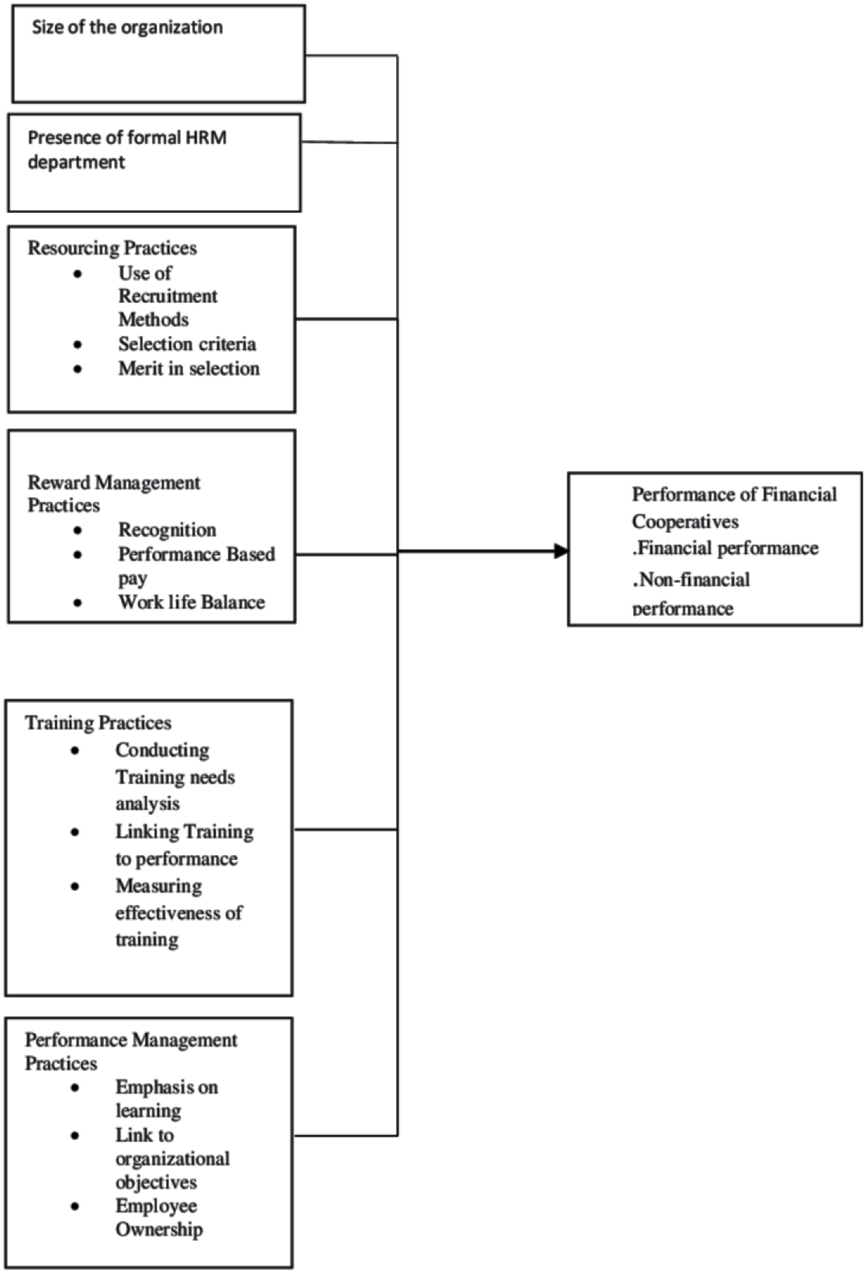

Figure 10. Network information table

Network Information			
Input Layer	Covariates	1	Synergetic relationship of HRM practices
		2	Employee resourcing practices
		3	Reward management practices
		4	Training practices
		5	Performance management practices
		6	Size of financial cooperative in terms of membership
		7	Presence of formal HRM department
	Number of Units[a]		7
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		4
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Financial performance
		2	Non-financial performance
	Number of Units		2
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias uni

Figure 11. Model summary

Model Summary			
Training	Cross Entropy Error		110.341
	Average Percent Incorrect Predictions		19.6%
	Percent Incorrect Predictions for Categorical Dependents	Financial	16.3%
		Non-Financial	23.0%
	Stopping Rule Used		1 consecutive step(s) with no decrease in error[a]
	Training Time		0:00:00.31
Testing	Cross Entropy Error		45.874
	Average Percent Incorrect Predictions		17.5%
	Percent Incorrect Predictions for Categorical Dependents	Financial	14.0%
		Non Financial	21.1%

a. Error computations are based on the testing sample.

Figure 12. Parameter estimates

Parameter Estimates										
		Predicted								
		Hidden Layer 1					Output Layer			
Predictor		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	[pbvii=3.00]	[pbvii=4.00]	[pbviii=3.00]	[pbviii=4.00]
Input Layer	(Bias)	.093	.158	-.495	-.506	-.617				
	Pbii	.056	.558	-.259	-.597	-.206				
	Pbiii	-.048	.089	-.535	.088	-.478				
	Pbiv	.529	-.051	-.271	.169	-.601				
	Pbv	.365	-.153	-.900	-.143	.070				
	Pbvi	-.164	.050	.069	-.302	-.345				
	q1	.075	-.183	.110	-.149	.118				
	q2	-.543	-.564	-.160	.149	-.130				
Hidden Layer 1	(Bias)						-.122	.855	-.091	.281
	H(1:1)						-.536	.371	.168	-.154
	H(1:2)						-.738	-.115	-.273	.635
	H(1:3)						.439	-.102	.483	-.688
	H(1:4)						.355	.321	.251	.185
	H(1:5)						.989	.177	.502	-.559

Figure 13. Non-financial classification

Non-Financial				
		Predicted		
Sample	Observed	Low Retention	High Retention	Percent Correct
Training	Low Retention	25	20	55.6%
	High Retention	11	79	87.8%
	Overall Percent	26.7%	73.3%	77.0%
Testing	Low Retention	12	8	60.0%
	High Retention	4	33	89.2%
	Overall Percent	28.1%	71.9%	78.9%

Figure 14. Financial classification

Financial				
		Predicted		
Sample	Observed	Low	High	Percent Correct
Training	Low	21	15	58.3%
	High	7	92	92.9%
	Overall Percent	20.7%	79.3%	83.7%
Testing	Low	7	4	63.6%
	High	4	42	91.3%
	Overall Percent	19.3%	80.7%	86.0%

Figure 15. Overall accuracy

Overall Percent Correct	
Sample	Overall Percent Correct
Training	80.4%
Testing	82.5%

Figure 16. Area under curve

Area Under the Curve		
		Area
Financial	Low	.875
	High	.875
Non Financial	Low Turnover	.855
	High Turnover	.855

Figure 17. Variable importance

Independent Variable Importance		
	Importance	Normalized Importance
Employee resourcing practices	.237	100.0%
Reward management practices	.174	73.5%
Training practices	.083	35.1%
Performance management practices	.201	84.9%
Synergetic relationship of HRM practices	.154	64.7%
Size of financial cooperative by membership	.070	29.4%
Presence of Formal HRM department	.080	33.8%

Figure 18. Reliability statistics

Variable	Number of items	Cronbach's Alpha (α)
Financial Performance	10	0.857
Non -Financial Performance	9	0.602
Training Practices	10	0.833
Performance Management Practices	10	0.871
Resourcing Practices	10	0.881
Reward Management Practices	10	0.859
Synergetic Relationship	10	0.878

Figure 19. Financial performance KMO Bartlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.833
Bartlett's Test of Sphericity	Approx. Chi-Square	822.542
	Df	36
	Sig.	.000

Figure 20. Financial performance communalities

Communalities	Initial	Extraction
There will be an increase in net profit in the foreseeable future	1.000	.680
There has been an increase in net profit this financial year compared to other years	1.000	.740
Net profit realized is adequate to pursue organizational vision	1.000	.579
Net profit realized is adequate to enable investment in Human Resources	1.000	.625
Net profit realized meet shareholders expectations	1.000	.658
Net profit realized enables the organization meet SASRA requirements	1.000	.468
Net profit realized is within organizational targets	1.000	.512
Net profit realized enables the organization to meet its financial obligations	1.000	.583
Net profit realized is enough to enable the organization adequately invest in increasing market share	1.000	.700

Extraction Method: Principal Component Analysis.

Figure 21. Non-financial performance KMO and Bartlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.763
Bartlett's Test of Sphericity	Approx. Chi-Square	379.567
	Df	36
	Sig.	.000

Figure 22. Non-financial communalities

Communalities

	Initial	Extraction
Rate of employees leaving has been reducing over the years	1.000	.406
Most employees want to remain in this organization in the foreseeable future	1.000	.656
Managers are concerned about employee leaving the organization	1.000	.094
Mangers investigate why employees leave this organization	1.000	.436
Rate of employees leaving does not affect smooth operations of the organization	1.000	.492
Managers work towards reducing rate of employees leaving	1.000	.563
In the coming years the rate of employees leaving the organization will go down	1.000	.447
Managers address issues that make employees leave the organization	1.000	.647
HR policies address the need to retain employees	1.000	.516

Extraction Method: Principal Component Analysis.

Figure 23. Resourcing practices KMO and Bartlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.883
Bartlett's Test of Sphericity	Approx. Chi-Square	1037.558
	Df	45
	Sig.	.000

Figure 24. Resourcing practices communalities

Communalities	Initial	Extraction
"Recruitment and selection is done in an extensive manner in this organization (uses of a combination of methods)"	1.000	.622
I would rate our selection criteria highly in making credible selection decisions	1.000	.643
I would rate this organization highly in terms of using merit in the selection process	1.000	.593
I would rate our recruitment and selection methods very highly in acquiring employees who share our values	1.000	.648
Our recruitment methods usually methods usually lead the right candidates for the job	1.000	.656
Our selection tools enables us to get the best candidates for the position	1.000	.612
Incase talent is not available within the organization, external recruitment is done	1.000	.680
Incase talent is available within the organization, internal recruitment is done	1.000	.436
Recruitment process can be aid to be said to be cost effective in this organization	1.000	.741
Selection criteria are well known in this organization	1.000	.420

Extraction Method: Principal Component Analysis.

Figure 25. Reward management practices KMO and Bartlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.825
Bartlett's Test of Sphericity	Approx. Chi-Square	895.594
	Df	45
	Sig.	.000

Figure 26. Reward management practices communalities

Communalities

	Initial	Extraction
The organization uses recognition schemes to reward outstanding employees	1.000	.715
The organization uses recognition schemes to reward outstanding teams	1.000	.654
Salary increases and promotions are linked to performance Management systems	1.000	.606
Employees have the time to attend to other matters of life beside work	1.000	.627
Compared to other organizations we are competing with, our organization has good pay levels	1.000	.684
Managers acknowledges individual and team performance	1.000	.589
Employees balance work and personal responsibilities	1.000	.776
Management is supportive of employees' efforts to balance work and personal responsibilities	1.000	.744
The organizations uses both financial an non financial rewards	1.000	.686
Rewards are designed to improve organizational performance	1.000	.699

Figure 27. Training practices KMO and Bartlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.822
Bartlett's Test of Sphericity	Approx. Chi-Square	689.549
	df	45
	Sig.	.000

Figure 28. Training practices communalities

Communalities

	Initial	Extraction
Before any training this organization conducts training needs analysis	1.000	.767
Training done to employees is informed by organization objectives	1.000	.757
Evaluation of training effectiveness is done extensively during, before and after training	1.000	.666
Training is geared towards increasing organizational performance	1.000	.628
Training is used as a solution for performance problems	1.000	.716
The organization has a structured way for evaluating training	1.000	.457
Employees do value training they receive in this organization	1.000	.639
Training done to this organization is geared towards meeting customer needs	1.000	.591
After training, the organization is geared towards meeting customer needs	1.000	.739
Within the organization there is an enabling environment for transfer of training to thrive	1.000	.425

Extraction Method: Principal Component Analysis.

Figure 29. Performance management KMO and Bartlett's test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.887
Bartlett's Test of Sphericity	Approx. Chi-Square	747.224
	Df	45
	Sig.	.000

Figure 30. Performance management practices communalities

Communalities

	Initial	Extraction
When performance management data is discussed with employees, emphasis is placed to learning in cases where there is a performance gap	1.000	.321
There is link between the performance management system and organization objectives	1.000	.435
In this organization performance management is done as consultative process between managers and employees	1.000	.508
Performance targets are implemented in this organization	1.000	.580
There are personal development plans to underpin achievement of performance targets	1.000	.374
Performance targets are in line with job descriptions	1.000	.476
Performance management in this organization aims at improving individual and team performance	1.000	.523
Performance Management is treated as a continuous process taking place throughout the year as opposed to annual appraisals	1.000	.495
Performance management in this organization is forward looking	1.000	.516
Performance Management System is well understood by employees	1.000	.441

Extraction Method: Principal Component Analysis.

Figure 31. Synergetic relationship KMO and Bartlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.885
Bartlett's Test of Sphericity	Approx. Chi-Square	841.122
	df	45
	Sig.	.000

Figure 32. Synergetic relationship communalities

Communalities	Initial	Extraction
Immediately after recruitment and selection people are trained on organizational policies and procedures	1.000	.587
Performance management data is used in making training decisions in the organization	1.000	.538
Performance management data is considered when awarding financial and non financial rewards	1.000	.463
Training is seen as one of the rewards in this organization	1.000	.425
Employees are trained on how performance management system works	1.000	.499
HR policies ensure the organization recruits employees who can easily be trained	1.000	.434
HR policies ensure that training offered in this organization is aimed at achieving organizational goals	1.000	.443
Employees selected in this organization fit its ability to pay	1.000	.344
HR policies ensure that Performance management system in this organization is aimed at achieving organizational goals	1.000	.464
HR policies ensure that reward management in this organization is aimed at achieving organizational goals	1.000	.623
Extraction Method: Principal Component Analysis.		

CONCLUSION

The neural network model was found to be effective in prediction of financial and non-financial performance. Most financial cooperatives are predicted to have high retention and high financial performance. This indicates that membership number, presence of formal HRM department, training practices, reward management practices, performance management practices, resourcing practices and synergetic relationship of HRM practices are predictors of financial and non-financial performance in financial cooperatives. Four predictors had elevated importance in predicting both financial and non-financial performance. These include employee resourcing practices, performance management practices, reward management practices and synergetic relationship among HRM practices. Additionally, there are considerable number of financial cooperatives with low retention levels and low financial performance. There is dearth of researches linking HRM practices and performance using ANN.

Implications for Knowledge

This study contributes to the limited knowledge available on ANNs in HRM across firms as well as HRM in financial cooperatives. Most studies on HRM and performance generally and the ones using ANN done in other sectors largely ignore the influential sector of cooperatives. In addition, this study has focused on another ignored factor in HRM-performance link- synergetic relationships among HRM variables and found it to be a predictor of financial and non-financial performance of cooperatives. In addition, it demonstrates how HRM research in cooperatives using ANN should be analyzed and reported. The study focuses attention to use of ANN as a tool for cooperatives management and research alongside other statistical approaches.

Practitioners and Managerial Implications

For HRM financial practitioners and managers, the importance of ANN has been confirmed by this study and others as well. In line with this, the researcher calls for managers to acquire skills in ANN so as to apply them in solving organizational phenomena. Unless both researchers and practitioners have skills in ANN, implementation of research findings will be difficult. Both financial and non-financial strands of performance must be given equal attention as they are important in overall performance. Financial cooperatives' managers in Kenya must concentrate on formalizing HRM practice within HRM departments as well as increase membership of these organizations. These managers must prioritize reward management practices, synergetic relationship of HRM practices, performance management practices, resourcing practices and training practices – linking them together, so as to improve performance. Managers of financial cooperatives with low retention and low financial performance should implement appropriate HRM practice, depending on organizational stage of development. Improvement of HRM practices where necessary is also important. Practitioners will find this research important in the sense that it demonstrates the value of data science in general and ANN in particular to management of cooperative resources. Researchers will also find this study important as it demonstrates how to analyze and report findings using ANN. The study will be like a pedestal as HRM field marches on towards fully towards utilizing the breadth of power as far as data science is concerned. Cooperatives cannot be left out in HRM and data science discourse.

CONFLICT OF INTEREST

The author of this publication declare there is no conflict of interest.

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