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An Artificial Neural Network Model for Industry-University Collaboration Failure Prediction Based on Psychological Risk Factors

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Abstract— Industry-University collaborations are known to offer firms a competitive edge by giving them access to a diverse range of complimentary resources outside the confines of their organisations. However, failure in these collaborations is a common problem. Failure can result in a waste of resources delays in meeting customer demands and therefore it is undesirable. One major risk category associated with failure is psychological risks. The concept of change triggers negative responses amongst employees and therefore can affect the performance of these collaborations. Detecting these risks early can help managers mitigate them and take steps necessary to ensure success. In this paper, an Artificial Neural Network approach is used to reduce industry-university collaboration failure by predicting failure. The Artificial Neural Network employed to build the models is the Multi-perceptron neural network and it is applied to two different datasets, one imbalanced and the other one balanced through means of a the Synthetic minority oversampling technique algorithm. The results reveal that the Multi-perceptron model built with a balanced dataset are better at predicting industry-university collaboration failure as compared to the one built with the raw imbalanced dataset.

Keywords— Industry-University Collaboration, Artificial Neural Networks, Risk Prediction, Psychological Risk, Innovation.

I. INTRODUCTION

As organizations are progressively being faced with tough global competition, it is increasingly becoming paramount for them to stay ahead of competition (Moaniba, Su and Lee, 2019). One outstanding source of competitive edge is Industry-University collaboration (IUC) (de Wit-de Vries et al., 2019). Organisations that collaborate with universities get to exchange ideas and share resources with their partners to meet the ever changing market needs (Jiravansirikul, Dheandhanoo and Chantamas, 2017). This gives these organisations a competitive advantage due to access to diverse specialized human capital and advanced infrastructure (Aliasghar, Rose and Chetty, 2019). They can also enhance their innovation speed by splitting labour among partners (Jiao et al., 2019). Furthermore these collaborations reduce the likelihood of mistakes, which are known to cause delays in new product delivery. Shorter product innovation time is desirable since it can assist in gaining the first-mover advantage, establishing early market segments and as well as gaining customer loyalty (Vega, 2013). In essence, IUCs are increasingly important and it is in the interests of all the involved actors that such collaborations are successfully implemented (Li and Huang, 2018).

However, many organizations find it difficult to establish thriving IUCs (Awasthy et al., 2018). In their work (Bidault and Castello, 2010) discovered that approximately 50-80% of "co-innovation" projects end up in failure.

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This can be attributed to the fact that industry and universities have varying objectives, working habits, cultures and experience different constraints (Yilmaz, Won and Seok, 2017), (Hitchen et al., 2017).

IUCs demand breaking the habit of silo based innovation in order to fit within the new realities of innovation (Ortiz et al., 2019). Generally, the psychological process of facing change triggers a negative attitude. People tend to be comfortable with a conversant situation as opposed to an unknown future (Day, Crown and Ivany, 2017). Particularly, changes regarding changes in the job role are linked to an increased resistance as they tend to stimulate insecurities with reference to the continued existence of the job (Day, Crown and Ivany, 2017). In essence, several organizations are faced with resistance to change as innovation is rapidly being practiced with external partners (Luiza et al., 2014), (Wal, Criscuolo and Wal, 2014).

Therefore it is important to detect the likelihood of resistance upfront, to avoid IUC failure and increase the chances of success. It is in this light that this paper develops an Artificial Neural Network (ANN) model to predict IUC failure based on Psychological risk factors, in the context of Botswana. The findings of the study are envisioned to assist in managing these risks upfront so that an overall action plan can be devised to mitigate them.

II. LITERATURE REVIEW

For IUCs implementation, the not-invented-here (NIH) syndrome has been cited as one of the greatest challenges of collaborative innovation (Vrande, Jong and Vanhaverbeke, 2009), (Hua, 2012). NIH translates to negative attitudes towards knowledge developed externally (Luiza et al., 2014).

Generally, because employees feel threatened by external ideas and in turn deliberately devalue them so as to encourage in-house capabilities. Essentially, employees deem internal ideas more valid than use knowledge sourced outside the confines of an organization. Therefore they resist change (Cheng et al., 2013) which can be a tremendous hindrance to IUC success.

A case study research by (Fernandes, O'Sullivan and Luis Miguel D.F, 2022) outlined the barriers facing IUCs in the Portuguese context. The challenges identified include uncertainty surrounding working methods, contradictory expectations, performance measurement, and geographic distance.

Research by (Rybnicek and Königsgruber, 2019) performed an extensive a literature review on 103 IUC papers in order to single out factors that impact the success of these partnerships. The study mentioned relationship factors as one of the major success factor categories.

With respect to relationship factors, good and frequent communication both at the top and operational level, were noted as the basis for enabling fruitful IUC partnerships. The study also cited the importance of commitment to IUC success. Similarly, attitude towards IUCs influences commitment. For instance researchers are highly likely to commit to IUCs with industry partners that have a positive attitude towards IUCs.

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A survey conducted in Malaysia measured IUC success during the R&D development phase (Ramli and Senin, 2021).. The study highlighted goal compatibility and sharing the same collaborative objective as key in determining the success of a collaborative project.

A. Industry-University Collaboration and Psychological Risk

While industries and universities engage in collaborative partnerships, their institutional differences cannot be overlooked. These differences emanate from multiple coexisting institutional logics (norms, rules and beliefs) that shape how decisions are made (Abdelrehim, Linsley and Verma, 2017). IUCs demand a change of behaviour, developing of new working relationships and engaging in new responsibilities demanded (Wal, Criscuolo and Wal, 2014), (Podmetina et al., 2018). Failure to do so may result in unsatisfactory IUC outcomes (Attia, 2015). This builds upon the organizational inertia theory. Previous literature refers to organizational inertia as inadequate adaptation to fluctuations in the environment (Cheng et al., 2013). However, this study instead looks at inertia through the lens of an individual employee. This is due to the fact that employees are amongst firms' greatest assets and they are the implementer of innovative ideas (Chesbrough & Brunswicker, 2013), (Larawan, 2011). If individual employees are not prepared to accept and share knowledge with partnering firms, the success of IUC may be compromised. Therefore this study seeks to develop an ANN model for predicting IUC failure based on psychological risk factors.

B. An Overview of Artificial Neural Networks

ANNs are powerful machine learning algorithms that process large amounts of data by mimicking the human brain thinking and learning functionalities (Hakimpoor et al., 2011), (Umayaparvathi, 2012). ANNs are capable of learning complex trends and patterns in data and subsequently generalize the learned data. They perform multiple tasks such as predictive modelling, classification, and clustering. The ANN structure consists of a myriad of processing nodes known as neurons. Neurons accept input data from outside the ANN's ecosystem, process it using a transfer function and then transmit the output to other neurons. This is made possible through a number of layers that ANN have. The first layer is called the input layer, the second layer is called the output layer and the inner layer (s) is called the hidden layer (Hakimpoor et al., 2011). The structure of a typical ANN is illustrated in Fig.1 below.

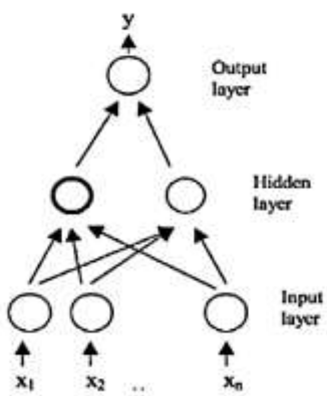

Figure 1: A typical Neural Network Structure

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III. METHODOLOGY

The aim was to model psychological risk factors that can potentially affect IUC failure so as to predict new cases. In order to accomplish this an ANN approach was used and the modelling procedure as well as the datasets used are discussed in this section.

A. Study Instrument

Psychological risk was measured by 6 components as shown in Table 1. A five-point Likert scale questionnaire ranging from 1 denoting "Very high occurrence" to 5 "No occurrence" was used. Respondents were asked to rate a grade for each risk variable by considering to what extent their company in recent years has had a negative impact while collaborating with universities, because of the variable presented.

Table 1: Measurement of psychological risk

Label	Item
PSYCR1	Resistance to external ideas and partners
PSYCR2	Anxiety towards change
PSYCR3	Finding internal ideas more valid than knowledge sourced outside the organization and resistance to testing ideas outside our company
PSYCR4	Feeling left out during collaboration with universities
PSYCR5	Lack of commitment to collaborative projects due to fear of change
PSYCR6	Threatened by change in job roles and responsibilities

IUC failure was measured in terms of number of new product launches. Product launches, is a valuable proxy for IUC performance measurement. It assesses the number of new product launches, improved products or projects as a result of the alliance (Nunes and Abreu, 2020).. Measuring this can help in accounting for impact of IUC.

A five-point Likert scale questionnaire ranging from 5 denoting "Very low" to 1 "Very high" was used. Respondents were asked to rate the relative number of products that have been launched during IUCs based on the psychological variable.

B. Dealing with Imbalanced Data

The dataset consisted of a total of 182 responses and was highly imbalanced in the sense that the majority class (High) had significantly larger instances compared to the other two classes (low and medium). Class label "high" had 166 instances, class label "low" had 10 and class label "medium" 6 as shown in Table 2.

Developing models when there is data imbalance can be challenging since the classifier will most likely classify majority instances as belonging to the class with the highest count (Hange et al., 2018), (Hadianfard et al., 2021). Therefore to counter this problem, the Synthetic minority oversampling technique (SMOTE) algorithm was employed.

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Table 2: IUC Failure frequencies per class

Class Label	Count
High	166
Low	10
Medium	6
Total	182

SMOTE is a technique that oversamples the minority class by generating “synthetic” examples based on the k nearest neighbor of the class (Chawla et al., 2002). This paper used 5 nearest neighbours which is the default in the Waikato Environment for Knowledge Analysis (WEKA) workbench,

C. Artificial Neural Network Model Building

The modelling of IUC failure risk factors is achieved through the utilization of ANNs. This study makes use of the Multi-layer perceptron (MLP) ANN, a feed forward ANN. In a feed forward network information only moves forward without feeding back to the previous layers (Thota and Changalasetty, 2013).Thus from input to hidden and lastly output layer. An MLP-ANN uses a back-propagation to train an ANN how to carry out different tasks as classification, clustering and predictions. MLP-ANN is a supervised learning algorithm that takes the input data examples as well as the supplied desired output class and is assessed based on how good or bad it recognizes classes.

MLPs are suitable for this study as they are powerful algorithms especially when the data has a large degree of interdependence (Hakimpoor et al., 2011). A further rationale for using ANNs is that their performance is not impacted by multicollinearity as compared to other methods like partial least squares. ANNs can handle data with a lot of noise and when large computational rate are needed. Lastly, ANNs have the capability to detect nonlinear relationships in the input data sets and do make any preconceived assumptions about the data (Isaac, Jantan and Esther, 2018).

D. Multi-Layer Perceptron Neural Network Evaluation

As novel models are constructed, it is essential to evaluate their performance to direct research in promising trajectories. The performance of machine learning algorithms is generally assessed using predictive accuracy. However, this is not appropriate when the dataset is imbalanced (Chawla et al., 2002). Therefore in this paper the evaluation metrics used are sensitivity and specificity.

Sensitivity is also known as the true positive rate (TPR) or recall; this is the ratio of the number of positive instances classified over all the positive instances (Chawla et al., 2002). Sensitivity = True Positive (TP)/True Positive (TP) + False Negative (FN)).

$$Sensitivity = \frac{TP}{TP + FN} * 100$$

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Where TP (true positive) is the number of positive instances that were indeed correctly predicted as positive.

TN (true negative) is the number of negative instances that were correctly predicted as negative instances. FP (false positive) is the number of negative instances that were incorrectly predicted as positive and FN (false negative) is the number of positive instances that were incorrectly predicted as negative (Chawla et al., 2002).

Specificity is used for the purpose of measuring the proportion of negative cases that were correctly classified as negative, which is 1—FP (False positive) (Chawla et al., 2002)or can be denoted as follows: Specificity = True Negative (TN)/True Negative (TN) + False Positive (FP).

$$Specificity = \frac{TN}{TN + FP} * 100$$

IV. RESULTS AND DISCUSSION

The modeling was done in two parts, by conducting two different experiments; one with the original imbalanced data and the other one with balanced data after applying the SMOTE algorithm. The results of the two experiments are presented and discussed below.

A. Experimentation one (Imbalanced data)

This experiment employed the original imbalanced dataset with 182 instances and 7 features. Out of the 182 instances a total of 173 was correctly classified as belonging to either high, low or medium IUC failure rate. On the contrary only 9 instances were misclassified. At first glance the results look promising, however they fail to reveal a depth analysis of what specific class labels were correctly classified or misclassified (Cios, William Moore and Moore, 2002). Therefore a summary of the sensitivity and specificity based on the test data are displayed in Table 3to revel more details.

Table 3: Performance output of MLP on the original dataset

Class label	Sensitivity/Recall	FP rate	Specificity (1-FP rate)* 100
High	98.2	0.375	62.5
Low	50.0	0.012	98.8
Medium	83.3	0.006	99.4
Weighted average	95.1	0.343	65.7

As illustrated in Table 3the MLP-ANN was able to classify instances as belonging to the class label high as opposed to the other labels. This is evidenced by sensitivity; class high=98.2%, followed by class medium with 83.3% and lastly class low with only 50%.

On the other hand, the specificity rates were as follows, class high had the lowest value of 62.5%, class low came second with 98.9% while class medium had the highest specificity of 99.4%, even though it varied slightly with class low.

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It is important to note that the MLP-ANN was struggling to recognize instances as belonging to class low and medium. This can be attributed to the class imbalance problem (Hange et al., 2018). This experiment was compared to the second experiment conducted with SMOTE.

B. Experimentation Two (Balanced data)

This experiment made use of the balanced dataset after applying the SMOTE algorithm to the original dataset, at 800%. The new dataset was made up of 422 instances and 7 features and the data was almost balanced as shown in Fig 2.

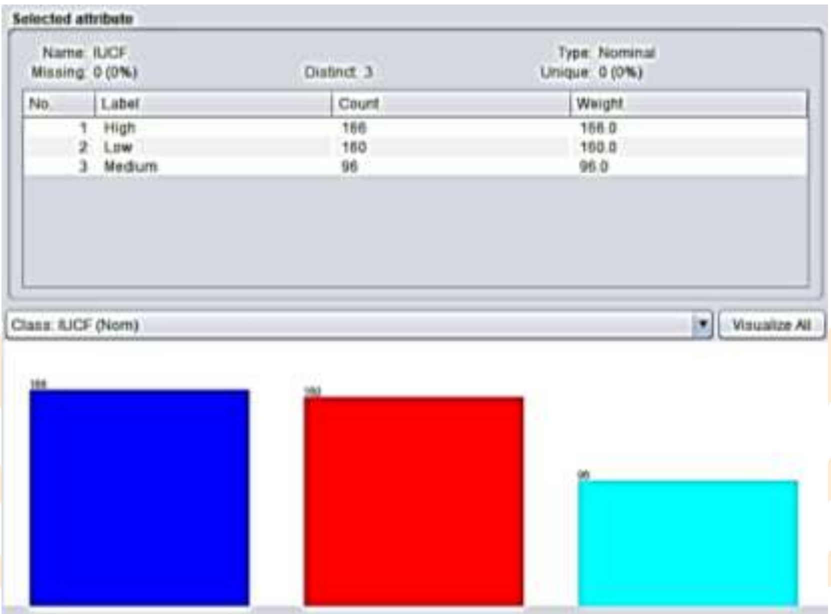

Figure 2: Dataset by SMOTE at 800%

As compared to the previous experiment, Table 4below shows that there was a slight decline in the sensitivity of class high (from 98.2% to 97.6%). However, there was a tremendous enhancement in the sensitivity for classes low and medium. In experimentation one, the sensitivity for class low was 50% and in experimentation two it was 96.9%. Thus there was an increase of 46.9%. Similarly, the sensitivity rate for class medium was 83.3% with imbalanced data and 99% with balanced data in experimentation two. Thus, the ability of the model to classify the instances as belonging to low and medium was enhanced and it can be concluded that the SMOTE algorithm enhances performance of the minority classes.

Table 4: Cross-validation results for SMOTE at 800%

Class label	Sensitivity/Recall	FP rate	Specificity (1-FP rate)* 100
High	97.6	0.023	97.7
Low	96.9	0.011	98.9
Medium	99.0	0.003	99.7
Weighted average	97.6	0.014	98.6

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When it comes to the Specificity rate for class high experimentation two, there was an improvement from 62.5% to 97.7%, class low had a slight improvement in specificity from 98.8% in experimentation one to 98.9 in experimentation two and lastly class medium specificity rate went from 99.4% to 99.7% in experimentation two.

We conclude that SMOTE improved the ability of the MLP-ANN to detect both the minority and majority classes based on the sensitivity and specificity values. Thus, models built with balanced datasets are desirable as compared to the ones with imbalanced data as shown in Table 5 below.

Table 5: Comparative Results between Experiments One & Two

	Experimentation one (Imbalanced)	Experimentation two (Balanced Data)
Sensitivity	95.1	97.6
Specificity	65.7	98.6

Experimentation two recorded the highest sensitivity and specificity values (97.6% and 98.6 %, respectively). Therefore this study recommends the MLP-ANN model from Experimentation two for predicting future IUC failure rates based on psychological risk factors.

CONCLUSIONS

The aim of the paper was to build an ANN model for predicting IUC failure based on psychological risk factors. IUC failure was measured using the number of patents and they were classified into either high, low or medium. The MLP-ANN was employed for this purpose.

The model building was accomplished through two experiments based on an imbalanced dataset and another on a dataset balanced through the SMOTE algorithm. Both experiments yielded promising result however, Experiment two proved that models built with balanced datasets yielded better results.

This is evidenced by experiment two which had superior sensitivity (97.6%) and specificity rates (98.6%) as opposed to experiment one with sensitivity (95.1%) and specificity (65.7%) rates, when predicting new cases of IUC failure.

The outcome could be useful to managers for detecting and managing psychological risks associated with IUC failure and thus help improve IUC performance.

Even though the results are quite useful, they can be further improved by using larger datasets and other ANN algorithms can be tested to see which ones perform better.

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