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How Artificial Intelligence can be used in International Human Resources Management: A Case Study

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ABSTRACT

Objective - Artificial Intelligence (AI) tools are becoming more accessible and more manageable in terms of practical implementation, enabling them to be used in many new areas, including the selection of international managers based on their international experience. The choice of personnel in a global environment is a challenge that has been the subject of heated debate for decades, both in practice and theory. Wrong decisions are cost-intensive and possibly contribute to economic failure. The present study aimed to test machine learning algorithms - as sub-disciplines of Artificial Intelligence (AI) - on a low-coding basis.
Methodology/Technique – A fictitious use case with a corresponding data set of 75 managers was generated for this purpose. Its applicability in relation to personnel selection for an international task was tested. In the next step, selected AI algorithms were used to test which of these algorithms led to high prediction accuracy.
Finding – The results show that with minimal programming effort, the ML algorithm achieved an accuracy of over 80% when selecting suitable managers for international assignments - based on the international experience of this group of people. The linear discriminant analysis has proven particularly relevant, and both the training and validation data provided values above 80%. In summary, ML algorithms' usefulness and feasibility in personnel selection in an international environment could be confirmed.
Novelty – It could be confirmed that for implementing the manager selection, freely available algorithms in Python achieve sufficiently good results with an accuracy of 80%.

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1. Introduction

For companies today, as in the past, selecting suitable managers is an important basis for a company's success. In times of digitalisation and globalisation, proper selection is becoming increasingly important. In this context, whether AI algorithms can contribute meaningfully to selecting suitable people from many applications or own personnel.

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Furthermore, the question arises as to whether this selection is cost-effective, as SMEs, in particular, have to act cost-efficiently in economically challenging times. The Study will examine how artificial intelligence (AI) can be used for a practical application - in this case, the selection of suitable managers (EU, 2022) (Leogrande & Costantiello, 2021) (Vogt, 2021). This area is closely linked to the topic of International Experience (IE). International experiences in global business have already been discussed a lot. It has been shown that, among other things, certain personality traits and personal international experience as existing characteristics of people significantly influence managers' later decisions to work in a global environment (McDougall & Oviatt, 2000). Similar results were also obtained by (Krueger Jr et al., 2000). More than 30 years ago, many authors agreed that the cognitive style of an individual plays a decisive role in the decision-making process (Wiersema & Bantel, 1992) and thus directly or indirectly influences decisions in companies (Hodgkinson & Maule, 2002) (Hodgkinson & Sparrow, 2002). Therefore, understanding how managers think –concerning international business – is highly relevant and may explain certain decisions, e.g., selecting the ion of global markets (Shane & Venkataraman, 2000).

2. Literature Review

One of the early approaches to capturing personality traits that might be relevant to manager selection is based on (Hambrick & Mason, 1984) Upper Echelon Theory. Figure 1 illustrates the theory (Hambrick & Mason, 1984), in particular about international experience (IE):

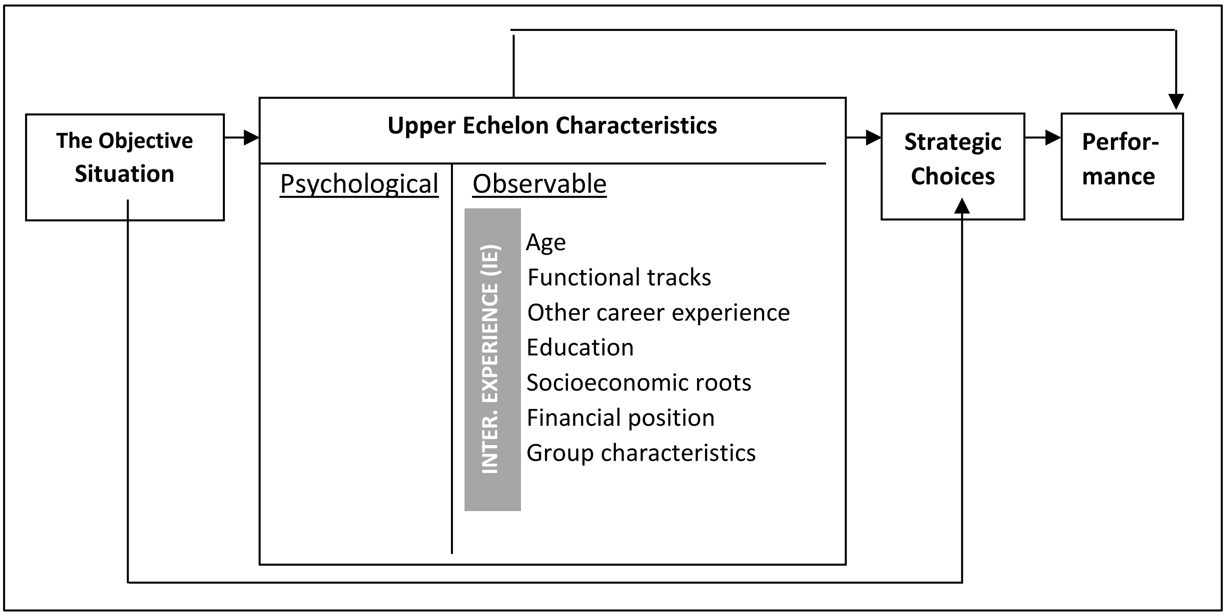

Figure 1. Upper Echelon Perspective of Organizations – Modified version adapted from (Hambrick & Mason, 1984)

Various studies have already been carried out on this (Ward, 2004) (West III, 2007) (Keh et al., 2002).

Studies show that this topic is still relevant (Ott & Iskhakova, 2019) (Parracho & Silva, 2021) (Wei et al., 2020) (Lukason et al., 2021). In other words, it is an issue that has been controversial for decades and is still relevant. However, the possibility of using artificial intelligence (AI) tools is new in the discussion. The number of publications is increasing, especially in business (Bickley et al., 2022). As a topic, AI itself is divided into various sub-areas, such as Machine Learning (ML) and Deep Learning (Kersting, 2018). A study (Kersting, 2018) defined AI and ML as follows: (a) Artificial Intelligence (AI), according to McCarthy (2007, quoted in Kersting, 2018): "…the science and engineering of making intelligent machines, brilliant computer programs. It is related to the similar task of using computers to understand human intelligence, but

AI does not have to confine itself to biologically observable methods…"; (b) Machine Learning (ML), according to Mitchell (1997, quoted in Kersting, 2018): "… concerned with the question of how to construct computer programs that automatically improve with experience …". Machine learning algorithms as a sub-field of artificial intelligence (Kavlakoglu, n.d.) and International Experience (IE) - How do they fit together? The answer is simple! Applying machine learning algorithms to measure International Experience (IE) offers advantages in terms of big data processing and predictive power. This leads to the next question: Have machine learning tools already been used to capture the International Experience? This question cannot be answered unequivocally. A search on this topic area reveals that there are only a few publications on this topic area. One of the few publications that have dealt with the topic came to the following conclusion:"… the results indicate that in prediction models, export experience variables are more valuable than general experience variables. Born globals can be predicted with an accuracy of at least 90% …" (Lukason et al., 2021). In other words, the authors applied various machine learning algorithms to predict the internationalisation type of a company based on the "export experience" - not directly comparable with International Experience (IE) - of the management (Lukason et al., 2021). As a result, the authors were able to determine: "... how useful managers' past general and export experience is in predicting whether young firms become fast internationalizers" (Lukason et al., 2021). The authors' findings are consistent with previous studies. For example, the results are the same as those of International Experience (Sommer, L., & Haug, 2013), but the focus on "Export Experience" (Lukason et al., 2021) leaves out an essential aspect of a person's International Experience (IE). Unfortunately, other studies in this environment were even less focused on the topic of International Experience (IE).

In summary, it can be said that there is still a need for clarification. Another important question related to AI and ML is their applicability in practice. Significant progress has been made here in recent years regarding relevance in practice. This affects the development of user-friendly AI tools and the possibility for users to adapt the relevant algorithms more quickly. More and more machine learning software packages allow the user to map their own algorithms - without prior programming knowledge. This enables the user to evaluate the theoretical principles from his or her perspective and then implement them in corresponding algorithms. In the following, a selection of suitable tools is presented that have proven easy to use in practice. Tool A is a low-coding-platform: "RapidMiner Turbo Prep makes it easy to get data ready for predictive modeling" (Miner, 2022). Further information on the usability of the tool for inexperienced users can be found in relevant videos (L Sommer, n.d.-b). Tool B is also a low-coding platform: "KNIME Analytics Platform is the open-source software for creating data science. Intuitive, open, and continuously integrating new developments, KNIME makes understanding data and designing data science workflows and reusable components accessible to everyone" (Knime, 2022). Quick solutions can also be worked out with the KNIME software, as shown in different videos (L Sommer, n.d.-a). Tool C is a special low-coding-platform from (Scikit-Learn, 2022): "It assumes a very basic working knowledge of machine learning practices (model fitting, predicting, cross-validation, etc.) …" (Scikit-Learn, 2022).

Based on the above literature review, a combination of the classical Upper Echelon approach of (Hambrick & Mason, 1984) with modern AI algorithms suggests itself. The following RQ research question can be derived:

Is it possible to train AI algorithms on the basis of various personnel data sets on international experiences in such a way that they can select suitable personnel for possible international assignments with a high level of accuracy?

To answer this question, the term "accuracy" (Lim et al., 2000) has to be defined: "…it is defined as the number of true positives and true negatives divided by the number of true positives, true negatives, false positives, and false negatives …" (DeepAI, 2019). In summary, two hypotheses can be derived concerning the research question, which contains a training data set on the one hand and a validation data set on the other. The first hypothesis considers the accuracy of the training data from selected algorithms. The target value is 80%, although the precise definition of a limit value for accuracy is controversial (Shafiq et al., 2018). The data split is 80:20. The following hypotheses were thus derived:

H1: *If a sufficiently large personnel data set is available for training, six ML algorithms can be trained so that each algorithm correctly identifies suitable personnel for international assignments with an accuracy of at least 80%.*

Because the so-called "Accuracy Paradox" (Brownlee, 2020) exists, it is sometimes necessary to consider other measurement variables – e.g., precision –. (Brownlee, 2020) describes the paradox as follows: "Sometimes it may be desirable to select a model with a lower accuracy because it has a greater predictive power on the problem". The second hypothesis pursues the goal of checking the accuracy of the algorithms using a validation theorem (Brownlee, 2020):

H2: *If a sufficiently large personnel data set is available for validation, one can identify suitable personnel for international assignments with more than 80% accuracy by using the best ML algorithm - according to hypothesis H1.*

3. Method

For the methodical implementation, on the one hand, a set of AI algorithms will be used to check external applicants or internal employees about their suitability as international managers. On the other hand, a fictitious data set will be generated to serve as the data basis for the algorithm test.

3.1 Case Study

The methodological implementation of the research question is based on a case study. For this purpose, a fictitious data set - based on an actual case study - is created and subsequently analyzed using machine learning algorithms. The case study can be described as follows: Company X wants to select employees for a foreign assignment. The personnel department uses the existing personnel data to determine suitable employees for an interview with the personnel department. From the company's point of view, employees with previous international experience are particularly interested in a personnel interview. The aim is to divide the employees into three groups at the end: Group 1 – International: Employees with relevant international work experience, preferably in the 20 - 35 age range. The international background is an advantage; Group 2 - Semi-International: Employees with international professional experience who have gained expertise between 35 - 45 years of age; Group 3 - National/Local: Employees without significant global knowledge or expertise in late business life (45 years and older). From the HR department's point of view, Group 1 - International is very well suited for the foreign assignment. The aim is to find the algorithm that selects exactly those people from the HR department's data who correspond to group 1.

3.2 Data Set and Algorithmen

For this purpose, a fictitious data set of 75 people - based on modified company data - is created (see annex). In the next step, this data set is examined with various machine learning algorithms - programmed in Python. Below is an overview in terms of approach, algorithms, and data:

- Approach: CRISP-DM from IBM for machine learning with Python is chosen for implementation (Brownlee, 2020) (Scikit-Learn, 2022) (IBM, n.d.): (1) Business & Data Understanding; (2) Data Preparation; (3) Modeling; (4) Evaluation; (5) Predictions.

- Algorithms: According to (Brownlee, 2020): (1) LR - Logistic Regression; (2) LDA - Linear Discriminant Analysis; (3) KNN - K-Nearest Neighbors; (4) CART - Classification and Regression Trees; (5) NB - Gaussian Naive Bayes; (6) SVM - Support Vector Machines.
- Data Set: The fictitious data set captures the International Experience (IE) of employees by, e.g., four selected criteria (Lutz Sommer, 2013): (a) Age - In which stage of life (= age) were IE gained? Early experience indicates interest in activities abroad (= high suitability for an international job); (b) Work_IE - International work experience in years. The more years, the higher the interest in international activities (= high suitability for an international job); (c) Study_IE - International study experience (e.g., stay abroad for years). The higher, the stronger the interest in activities abroad (= high suitability for an international job); (d) Background_IE - International background (e.g., living abroad for years). The higher, the stronger the interest to go overseas (= high suitability for an international job). The employees are classified - according to the four selected criteria - as "International, Semi-International and National/Local".

4. Results

In the following - according to the approach of (Brownlee, 2020) - the different ML approaches are applied to the case studies data.

4.1 Descriptive Statistics – Case Study

In the first step, descriptive statistics were carried out, and the data set was checked for possible outliers, consumption, or anomalies. Based on the data, the plausibility of the data could be confirmed, which was expected for a fictitious data set (see Appendix A.):

	age	work_IE	study_IE	background_IE
count	75.000000	75.000000	75.00000	75.000000
mean	41.360000	0.706667	0.56000	0.413333
std	10.989725	0.818260	0.49973	0.495748
min	21.000000	0.000000	0.00000	0.000000
25%	32.500000	0.000000	0.00000	0.000000
50%	40.000000	0.000000	1.00000	0.000000
75%	49.000000	1.000000	1.00000	1.000000
max	65.000000	3.000000	1.00000	1.000000

Typ	
International	25
Local	25
Semi_International	25

Table 1: Descriptive statistics about the data set of 75 people, described in Appendix A.

According to descriptive statistics in Table 1, we are dealing with the following people: (a) AGE: mean of 41.36 years (=range of 21 - 65 years); (b) Work_IE: Have work experience abroad with a mean of 0.71 years (= range from 0 to 3 years); (c) Study-IE: Early experience in Study and training with 0.56 years (= range of 0 - 1 year); (d) Background_IE: Other international experience is given with 0.413 years (= range of 0 - 1 year). All in all, it can be said that those presented have international experience to a relevant extent. The graphical evaluation of the data set provided the following representation:

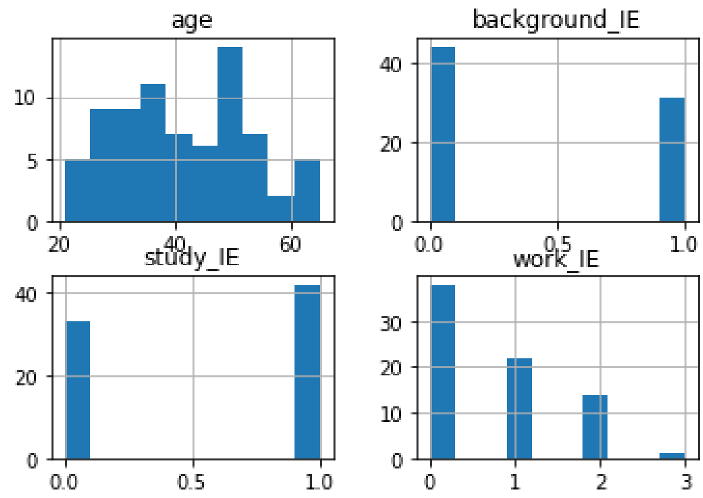

Figure 2: Descriptive statistics about the data set of 75 people, described in Appendix A.

The graphical description of the data sets in Figure 2 shows that they are not subject to a normal distribution. In other words, only the age values tend toward normal distribution. The other indicators show the following picture: (a) Study_IE: The majority of the 75 employees selected by the HR department have already gained experience abroad, at least during their studies or training; (b) Work_IE: The majority of the selected employees have no work experience abroad. However, some employees have 1 - 3 years of international work experience; (c) Background_IE: Background experience is low and reduced to a maximum of 1 year. It is recognised that in our fictitious example company, the HR department has already selected people with a particular international affinity and a comprehensive data set. For most German SMEs, this internationality profile would probably not be given.

4.2 ML Algorithms – Case Study

The six ML algorithms mentioned above were applied to the above data set (see Appendix A). For this purpose, on the one hand, the given codes of (Brownlee, 2020) were used; on the other hand, different codes for implementing the research question were programmed in Python. The following results were obtained based on a data set of 75 people (Appendix A.): LR: 0.866667 (0.100000); LDA: 0.916667 (0.083333); KNN: 0.850000 (0.157233); CART: 0.833333 (0.166667); NB: 0.866667 (0.124722); SVM: 0.866667 (0.145297). Figure 3 illustrates the results:

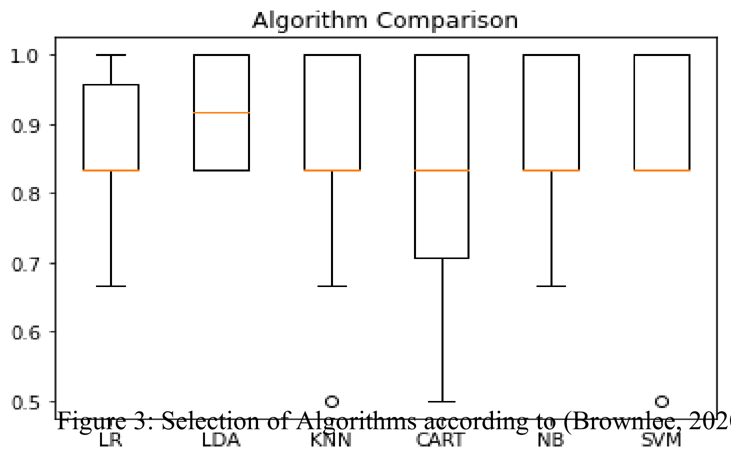

Figure 3: Selection of Algorithms according to (Brownlee, 2020)

The individual algorithms in Figure 3 show different estimated accuracies for the training dataset. The Linear Discriminant Analysis (LDA) achieves the highest value with 0.9166 or 91.66% (Brownlee, 2020). The importance of the other algorithms gained less than 87%. In the next step, a validation dataset is used to check the results of the selected LDA algorithm for this dataset (Lim et al., 2000) (Brownlee, 2020). The following figure shows that the accuracy is lower, i.e., 0.8 or 80 %. The following classification report provides an overview of the indicators "precision, recall and f1-score" (Brownlee, 2020):

```
0.8
[[3 0 0]
 [0 4 1]
 [0 2 5]]
                    precision    recall  f1-score   support

     International       1.00      1.00      1.00         3
             Local       0.67      0.80      0.73         5
Semi_International       0.83      0.71      0.77         7

          accuracy                           0.80        15
         macro avg       0.83      0.84      0.83        15
      weighted avg       0.81      0.80      0.80        15
```

Table 2: Classification Report according (Brownlee, 2020)

The results in Table 2 can also be interpreted by staff who are not experts. For this, we use the interpretation from (Choudhary, n.d.) as an example, which provides a superficial interpretation that is available to everyone on the internet, whereby these definitions are scientifically abbreviated but permissible (Scikit-Learn, 2022) (Lim et al., 2000): (a) Precision: "Precision is the ratio of correctly predicted positive observations to the total predicted positive observations" (Choudhary, n.d.). In our case, "International" is recognised very well, "National / Local" relatively poorly; (b) Recall: "Recall is the ratio of correctly predicted positive observations to all observations in actual class" (Choudhary, n.d.). The results are pretty good; (c) F1-Score: "F1 Score is the weighted average of Precision and Recall. Therefore, this Score considers both false positives and negatives" (Choudhary, n.d.). The results are also quite good.

The results align with the "export experience" research from Lukason, Vissak, and Segovia-Vargas (2021). These authors have also successfully demonstrated a similar international connection between experiences and the activities of a company via AI algorithms. Furthermore, it can be said that the AI algorithms that are available free of charge are a sensible and inexpensive alternative to software that can be purchased. Well-known analysis software packages with high-quality standards and user-friendliness can be at a monthly cost of $7,500 per month and user (Trust Radius, 2022). This can be a significant financial burden for SMEs.

5. Discussion

5.1 Hypothesis Testing

According to hypothesis 1, it was checked whether an accuracy of more than 80% was achieved for all 6 ML algorithms. The results show that all algorithms reached this value. The Linear Discriminant Analysis (LDA) got the highest value, over 90%. In this respect, the hypothesis can be confirmed. This was unsurprising as this was a fictitious data set, and a sure consistency could be assumed. In the fictional case study, the human resources department could have made sensible decisions concerning selecting suitable managers based on a comprehensive data set for a foreign assignment.

The present results also confirm – albeit just barely – with values greater than or equal to 80% accuracy for precision, recall, and F1 Score, the H2 hypothesis about the validation data set. In other words, even with the validation data collection, the LDA still provides relevant input for selecting suitable people for international assignments. In summary, it can be said that both hypotheses have confirmed the applicability of ML algorithms to personnel selection in international business.

5.2 Limitations

The following limitations occurred in the Study: (a) The still outstanding practical implementation/testing; (b) What is the data quality of the companies about personnel?; (c) Are the employees prepared to deal with low-coding software packages? (d) Do data protection issues stand in the way of the evaluation?; (e) Are people who would have been successful in a face-to-face interview excluded by the pre-selection?

Further studies with accurate data from HR departments are needed to clarify these questions. Furthermore, it is also recommended that in future studies on this topic, employees of HR departments work on corresponding ML tools to be able to test the practical implementation.

6. Conclusion

The above result shows that the chosen algorithm - Linear Discriminant Analysis (LDA) - has made a good prediction concerning the training and validation dataset. Furthermore, it can be stated that these algorithms identify suitable international managers with a high degree of accuracy without incurring high costs in terms of license fees for an AI app. Overall, the Study also proved that AI algorithms can be used by non-experts with little prior knowledge. In this respect, the trend is confirmed that AI algorithms are also becoming more and more interesting for SMEs.

What conclusions can be drawn from the case study: (a) The effort is manageable, and the options to derive other assignments (e.g., measuring digital literacy) are manifold; (b) Non-IT experts can already carry out such analyses with little effort. It is to be expected that further steps towards low-coding will take place in the future, and the use of ML tools in professional practice will become even more likely; (c) The pre-selection of suitable staff becomes easy; (d) The pre-selection of qualified personnel is made dependent on measurable criteria; (e) The inclusion of company-specific measures is feasible; (f) The costs for the acquisition of low-coding software packages are low.

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