# IPO Forecasting Using Machine Learning Methodologies : A Systematic Review Apropos Financial Markets in the Digital Era

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## Abstract

**Purpose :** With the goal of shedding light on the ways in which machine learning (ML) approaches are now being used in initial public offering (IPO) research, this systematic analysis assessed how well IPOs performed.

**Design/Methodology/Approach :** To evaluate the efficacy of ML approaches in IPO appraisal, 21 papers from the Scopus and Web of Science databases were analyzed using PRISMA.

**Findings :** The findings revealed that ML algorithms, including rough set theory, text analytics, fuzzy logic, XGBoost, random forest, SVM, gradient descent, and artificial neural networks, outperformed linear methodologies in IPO evaluation.

**Practical Implications :** The exclusion of other databases may result in the overlooking of pertinent research, even with the thorough insights obtained from studies within the Scopus and Web of Science databases. Moreover, a singular concentration on ML approaches could overlook more comprehensive viewpoints or other approaches that could provide insightful information on initial public offerings. However, by offering more precise and nuanced assessments of IPO performance, the use of ML algorithms in IPO research can improve organizations' ability to make decisions. Businesses can use innovative and hybrid algorithms to improve their market success rates by gaining deeper insights and making better decisions about IPOs.

**Originality/Value :** This review, which focused on the investigation of novel algorithms, offered insightful information about the caliber of ML methods in IPO appraisal.

*Keywords :* initial public offerings (IPOs), machine learning (ML), neural networks, SLR, deep learning, artificial intelligence (AI)

JEL Classification Codes : G11, G12, G14

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According to Füllbrunn et al. (2020), there is a worldwide aberration associated with underpricing, which is neither new nor unique to the domestic market. The gains that are achieved when an IPO's listing day price exceeds the offer price are discussed as very high. Accurate IPO pricing is crucial to minimize loss, even though corporations have opted to embrace these phenomena. This implies more accurate listing day price predictions and control of mispricing. Machine learning (ML) has begun to be studied for IPO listing price prediction since conventional methods have not been able to adequately solve the forecasting component.

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Abiodun et al. (2018) stated that artificial neural networks (ANNs) have garnered significant interest due to their ability to learn autonomously and mimic the functioning of the human brain.

ANN has gained recognition as one of the best and most widely applied approaches for prediction and classification issues over the past 20 years, particularly in the financial industry. Its desirable and appealing feature is its capacity to make the most use of all the data available for creating the structure without being constrained by any assumptions about parametric modeling. Also, since the quantum and complexity of data in the financial sector draw a parallel with the data this technique can handle, it becomes one of the easiest architectures to decode the underlying problems, with computers becoming inexpensive and expeditious.

ANNs are computational structures that mimic the structure of the human brain to decode poorly defined situations (Tkáč & Verner, 2016). The ability of these networks to solve problems is improved by emulating the neuron model of the human nervous system, which can process nonlinear input inside its black box. The tool has meritorious applications in forecasting, classification, financial analysis, credit scoring, and decision assistance.

With "neural networks" as their analytical instrument, writers in a variety of disciplines have added groundbreaking research to the body of literature. A few notable studies are those by Jain and Nag (1995) on initial offers, Altman et al. (1994) on banking and distress, Kaastra and Boyd (1996) on financial analysis, Chen et al. (2003) on stocks and bonds, and others. Additionally, recent studies such as Khosla and Tara (2019) have extensively analyzed the impact of artificial intelligence and robotics on industrial economies, highlighting the transformative potential of disruptive technologies in reshaping traditional business paradigms. Moreover, the impact of macroeconomic factors on the Indian stock market has been thoroughly examined by Nayak and Barodawala (2021), emphasizing the intricate dynamics between economic indicators and stock market performance.

The application of ANN as an analytical tool has been used in a variety of commercial and financial research studies, but it has not gained traction in the field of initial public offerings (IPOs). To precisely anticipate the listing day price and reduce underpricing losses for the firms, the best ML algorithms still need to be found. Additional machine-learning algorithms have been employed by a few writers, including ensemble models (Ross et al., 2021), random forest (Baba & Sevil, 2020), and support vector machines (SVM) (Basti et al., 2015). A detailed review of all the available research is necessary before deciding on the optimal strategy or solution for IPO mispricing.

As a result, this study attempts to assess the current state of ML model application in the IPO market and makes recommendations for future researchers to address issues in the current research using the methodology of systematic literature review (SLR).

By evaluating the state of ML model applications in the IPO market through an SLR, this study aims to close this gap. Through a comprehensive analysis of the current literature, this study seeks to shed light on the effectiveness of several ML approaches in IPO price prediction and suggest directions for future investigation. This research aims to establish a foundation for furthering our comprehension of IPO price dynamics and shaping future research paths by means of a meticulous examination of previous studies.

## Methodology

Kitchenham (2004) developed a methodology for conducting an SLR, using quality assessment (QA) as one of the criteria, which was applied by Tealab (2018) for forecasting non-linear time series using ANN. The same methodology that underpins this analysis has been used to systematically shortlist and assess research articles for their quality, enabling conclusions about the existing methods and the novelty of the model development for IPO price prediction throughout time.

Therefore, the goal of this work is to gather and evaluate the theoretical contributions made to the creation of ML models based on ANN and other methods to predict the listing day price of IPOs.

### *Search Process*

Using Scopus as the search engine and a manual search of published publications, the following key produced a total of 173 documents: TITLE-ABS-KEY "Machine Learning" OR "Artificial Neural Network*" OR "Neural Network*" AND "Initial Public Offering*" OR "IPO*" OR "IPO Underpricing" OR "Listing Gain." However, applying the criteria of subject area, language, and document type, the final number narrowed to 17 as all the ineligible records were removed through automation. Using the same key, Web of Science could retrieve five articles that coincided with the articles already identified by Scopus. Hence, these duplicates were removed. The following criterion chain was applied during the last search: TITLE-ABS-KEY ("Machine Learning" OR "Artificial Neural Network*" OR "Neural Network*" AND "Initial Public Offering*" OR "IPO*" OR "IPO Underpricing" OR "Listing Gain"). Additionally, there are limitations to (DOCTYPE, "ar"), (LIMIT-TO (SUBJAREA, "BUSI") OR (LIMIT-TO (SUBJAREA, "ECON"), AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SRCTYPE, "j"). The following criteria were used to determine the final number of articles that needed to be reviewed using the SLR-preferred reporting items for systematic reviews and meta-analyses (PRISMA) technique.

### *Inclusion and Exclusion Criteria*

The selection of articles on IPOs where any ML methodology has been used to forecast the listing price as well as the price after listing was the subjective criterion used for inclusion. The analysis has covered even the studies that used ML algorithms to identify parameters influencing the post-listing success of IPOs.

Two studies out of the 17 that were found using Scopus were not included since they had to do with business promotion and communication and had to do with the IPO market and its analysis. One research was unable to be retrieved out of the fifteen studies that were left. The final 14 papers that were found in the Scopus and Web of Science databases were combined with a few additional studies that were found through citation searching after duplicates were eliminated. A total of 13 studies were located by citation, searching the publications that were located in the aforementioned databases. However, six reports were not included in this compilation since they were part of conference proceedings rather than published works.

The complete outcomes of the PRISMA software-assisted paper screening process for inclusion in the structured literature review are displayed in the flowchart that follows, as seen in Figure 1.

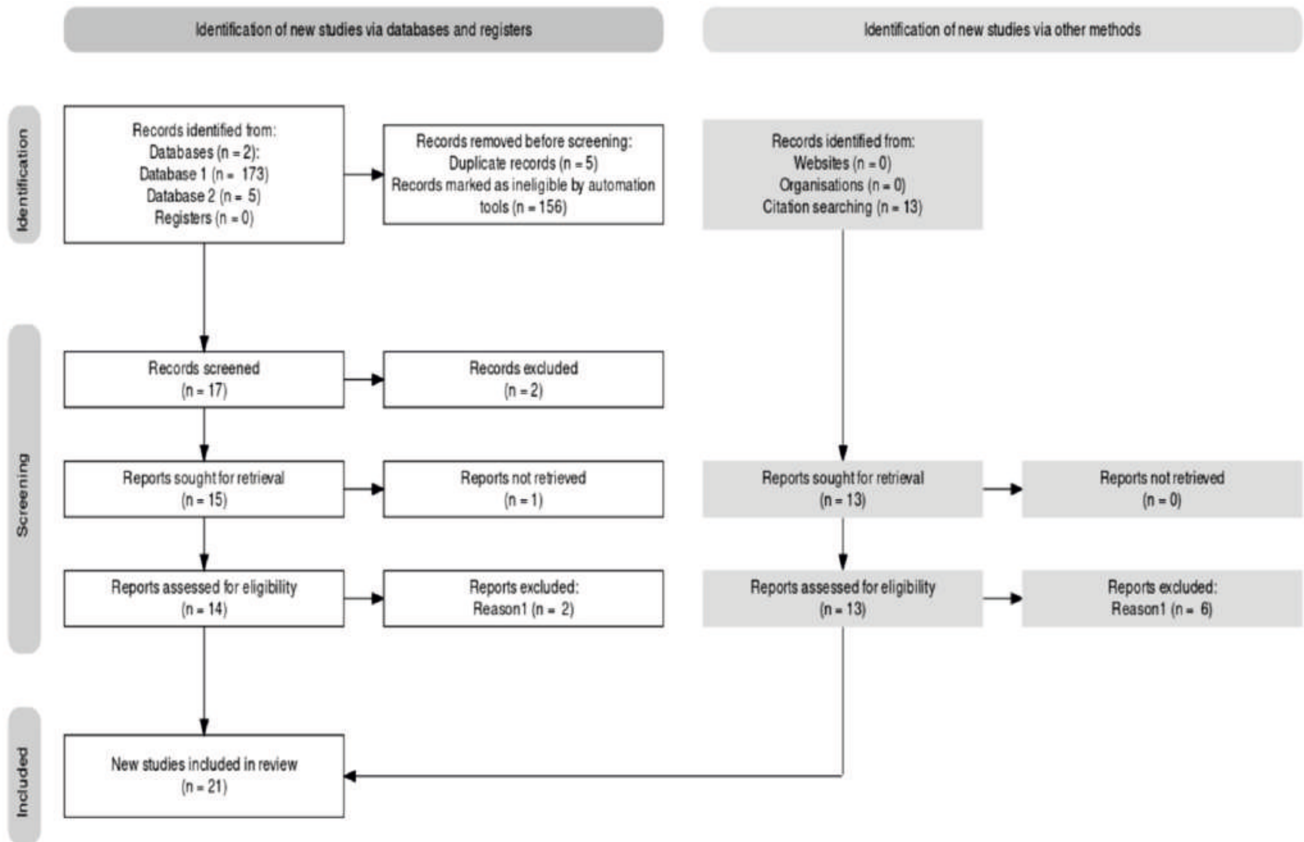
### *Explanation of the Flowchart*

The PRISMA technique's methodology is followed in the structure of the flowchart shown in Figure 1. The examined studies are arranged in three separate steps by the flowchart: identification, screening, and inclusion. The flowchart displays 173 studies that were automatically obtained from Database 1 (SCOPUS) after the pertinent keywords were entered into the database's search field. In addition to Scopus, Web of Science is another database used for document searches, yielding a total of five papers. All five of these publications were placed under duplicate records in the identification stage, though, because they coincided with the papers that Scopus had already retrieved (as illustrated in Figure 1).

After additional automated exclusions based on language, region, and publishing stage were applied to the research that Scopus had obtained, 156 papers were found to be ineligible, leaving us with 17 studies for the screening phase. These 17 studies, which were the search terms used in the Scopus database, represented the neural network selection criteria in the field of IPOs.

A citation search of the previously stated research turned up an extra 13 studies in addition to the databases. Two records were purposefully removed during the screening process because they did not fit the predetermined

**Figure 1.** *Flowchart Constructed Through PRISMA*




inclusion criteria. The studies did not represent the IPO market and were based on business communications and business promotions instead. A total of 14 papers had to be incorporated through databases for a systematic review because one study could not be retrieved from the database.

Six studies that were judged to be irrelevant were among the 13 that were found using citation search. Of them, two represented stock price prediction rather than IPO, and one was an SLR that was excluded because it could not pass quality testing using the study's criteria. Finally, three more studies were excluded as they were conference proceedings only and not published papers. In an SLR paper, published researches hold greater relevance.

After the entire screening, a total of 21 studies were included for the review, representing 14 from the databases and 7 from citations.

### *Quality Assessment*

The purpose of this study is furthered by the following set of questions that were developed based on the procedural application quality of the relevant methodologies, with an emphasis on the ANN model's development.

### *Quality Questions*

**QA1 :** Has the model been mathematically defined explicitly?

**QA2 :** Is there a systematic approach for the parameters used in the research to carry out the analysis?

**QA3 :** Have the variables been explicitly chosen as per their level of relevance?

**QA4 :** Has the quantity of layers, neurons, epoch sizes, and iterations been listed and determined methodically for the model's construction?

**QA5 :** Has the criteria to adjudge the accuracy of the model been defined in the study?

**QA6 :** Has the methodology been used, or is it proposed to be used, to assess the viability in a real-world scenario (TEST SET)?

**QA7 :** Has the training of the model (including data pre-processing) been done systematically with appropriate mention of the procedures?

The scores for questions were given on a scale of 0 to 1, where "0" represented the absence of particular criteria, "1" represented the present, and "0.5" represented the partial presence of the qualitative criteria in the study.

**QA1 :** A score of "1" here represents a complete and exclusive representation of formulas serving as a base for the entire model, whereas 0 represents its absence. In case the formulas have been defined but partially, then a score of 0.5 has been allotted.

**QA2 :** If the parameter estimate is justified procedurally, it takes the value of "1"; otherwise, it takes the value of "0." If references are limited to the existing literature, a score of 0.5 is given.

**QA3 :** Studies that provide a thorough justification for the inclusion of a certain variable in the research are assigned a score of "1," while studies that use other studies as a source for the selection of specific variables are given a score of "0".

**QA4 :** A study that strategically determines the complexity of the model will assign a value of 1; otherwise, 0 will be assigned. Methodological determinations are required on the number of layers to be included, the number of trials required, the epoch size, etc. If these guidelines were applied to earlier research, then 0.5 has been assigned.

**QA5 :** A value of 1 has been allocated if the study's model has been tested for accuracy using one or more criteria and the results have been justified, while 0 indicates that no accuracy testing has been done. A value of 0.5 is assigned to the accuracy testing if it has been demonstrated to be conducted implicitly or has been referenced in other research.

**QA6 :** Studies that demonstrate how the model is applied to the test set after being removed from the sample as a whole have been assigned a value of 1. The study has received a score of "0.5" under this evaluation in the event that the testing was only conducted in part and there was no clear justification. Zero has been assigned if the model has not been applied to a real case or the test set.

**QA7 :** If the study appropriately mentions the procedures and systematic process of training conducted, then it receives the value "1," otherwise "0." In case the training of the model has been implied or shown as a reference to other studies, then a value of 0.5 has been assigned for the same.

### *Supplementary Quality Criteria*

**QA8 :** The proportion of citations that a certain article has received throughout the publication. The amount of time that has transpired since the article's publication year is in the denominator, while the number of citations the article has received to date is in the numerator. It is suggested that in order to determine whether there is a relationship between the two, this QA criterion is correlated with the quality score acquired for the preceding seven criteria.

**QA9 :** SCImago Journal Rank (SJR) value for the journal in the year the relevant article was published.

### *Data Collection*

As part of the data-gathering procedure, the essential details from every research article were extracted, including the title, authors, primary objectives, and findings. The model's application and prediction power, impact factor, accuracy parameters' selection criteria, and SJR of the journal in the year the article was published were then assessed using a variety of tests.

## Obtained Results

### *Search Results*

**Table 1.** ***Quality Assessment of Published Research***

| ID | QA1 | QA2 | QA3 | QA4 | QA5 | QA6 | QA7 | No. of Citations | Year of Publication | Time Published | QA8 | TOTAL | SJR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 62 | 1995 | 27 | 2.30 | 6 | 1.07 |
| A2 | 1 | 1 | 0.5 | 0 | 1 | 1 | 0 | 6 | 2020 | 2 | 3.00 | 4.5 | 0.7 |
| A3 | 0 | 1 | 1 | 1 | 1 | 0.5 | 1 | 3 | 2021 | 1 | 3.00 | 5.5 | 0.61 |
| A4 | 0 | 1 | 1 | 0.5 | 1 | 0 | 1 | 2 | 2021 | 1 | 2.00 | 4.5 | 0.22 |
| A5 | 1 | 0.5 | 0 | 1 | 1 | 1 | 1 | 1 | 2021 | 1 | 1.00 | 5.5 | 0.26 |
| A6 | 1 | 1 | 1 | 0.5 | 1 | 0.5 | 1 | 1 | 2022 | NA | NA | 6 | |
| A7 | 0.5 | 1 | 1 | 0.5 | 1 | 0 | 1 | 13 | 2020 | 2 | 6.50 | 5 | 0.68 |
| A8 | 0.5 | 0.5 | 1 | 1 | 1 | 1 | 0.5 | 5 | 2018 | 4 | 1.25 | 5.5 | |
| A9 | 1 | 0.5 | 1 | 1 | 1 | 0.5 | 1 | 0 | 2015 | 7 | 0.00 | 6 | |
| A10 | 0.5 | 1 | 1 | 1 | 1 | 0.5 | 0.5 | 50 | 2015 | 7 | 7.14 | 5.5 | 1.87 |
| A11 | 0 | 0.5 | 1 | 0.5 | 1 | 0.5 | 1 | 10 | 2005 | 17 | 0.59 | 4.5 | |
| A12 | 1 | 0 | 1 | 0 | 1 | 0.5 | 0 | 12 | 2013 | 9 | 1.33 | 3.5 | 0.34 |
| A13 | 0.5 | 1 | 0.5 | 0.5 | 1 | 0.5 | 0 | 69 | 1996 | 26 | 2.65 | 4 | |
| A14 | 1 | 1 | 0.5 | 1 | 1 | 1 | 1 | 28 | 1996 | 26 | 1.08 | 6.5 | |
| A15 | 0.5 | 1 | 1 | 0.5 | 1 | 0.5 | 1 | 41 | 2001 | 21 | 1.95 | 5.5 | 0.75 |
| A16 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 15 | 1998 | 24 | 0.63 | 7 | 0.286 |
| A17 | 1 | 1 | 1 | 0.5 | 1 | 0.5 | 1 | 10 | 2016 | 6 | 1.67 | 6 | 0.6 |
| A18 | 0 | 0.5 | 1 | 0.5 | 1 | 0 | 1 | 13 | 2017 | 5 | 2.60 | 4 | 0.17 |
| A19 | 1 | 0.5 | 1 | 0.5 | 1 | 0.5 | 1 | 5 | 2012 | 10 | 0.50 | 5.5 | 0.31 |
| A20 | 0 | 0.5 | 1 | 0 | 1 | 0.5 | 1 | 4 | 2019 | 3 | 1.33 | 4 | 0.59 |
| A21 | 1 | 1 | 1 | 0.5 | 1 | 0.5 | 0.5 | 2 | 2014 | 8 | 0.25 | 5.5 | 0.41 |

### *Quality Assessment*

The type of ML algorithm used to assess underpricing and forecast first-day returns has been taken into consideration while analyzing the research published in the field of IPOs. Table 2 presents the conclusions of several research that have been published to date, with the first one appearing in 1995.

**Table 2.** ***Studies on IPO using Machine Learning Algorithms***

| ID | Author(s) | Year | Methodology | Objective | Findings |
|---|---|---|---|---|---|
| **A1** | Jain & Nag | 1995 | ANN | Using sensitivity analysis and the neural network technique, the sample 552 IPOs were priced. | The findings of the study confirm a reduction in underpricing of the IPOs, thus returning enormous gains through the usage of the ANN model. |
| **A2** | Colak et al. | 2020 | Generalized linear model (GLM), boosted generalized linear model (BGLM), gradient-boosted trees (GBT), and random forest (RF). | To review the market performance of US-listed Chinese firms w.r.t. the short run, long run, and w.r.t. regulatory delisting. To compare and contrast the predictive power of ML techniques such as gradient boosting and random forest over traditional linear and logit models. The study's goal is to investigate the factors contributing to the failure of Chinese companies that choose to list on US stock exchanges despite the potential advantages associated with US listing. This analysis is carried out from three different angles: the risk of regulatory delisting, particularly the danger of an IPO failing; short-term market phenomena like underpricing; and long-term market phenomena such as stock underperformance after issue. | The conclusion of this study tends to point out the fact that failed Chinese enterprises tend to experience more severe owners-related agency issues since they chose unreliable US middlemen, while going public. This is the reason why they failed in the first place. |
| **A3** | Ross et al. | 2021 | Combining random forest, XGBoost, K-nearest neighbors, and deep learning. | Whether there is enough information in the publicly available data of companies that it can predict whether that start-up will succeed or fail, success has been judged through the exit of IPO or acquisition of the company. Also, another objective is to identify whether ML models can predict whether the firm will get follow-on funding or not. | The authors have developed an ML model called CAPITALVX, which has proven to give four times more accuracy in the prediction of the exit scenario of an IPO, as compared to a venture capitalist. Such ML learning models can even identify whether it is a good investment or not, hence making investment decisions faster. |
| **A4** | Singh et al. | 2021 | ANN: Multi-layer perceptron (MLP). | This study seeks to comprehensively analyze the multitude of variables that influence post-IPO pricing and | The findings indicate that while fundamental issues become more significant over time, |

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| | | | | assess their relative importance. It specifically seeks to compare the performance of the stock at three different intervals following the listing: three months, six months, and twelve months. By doing this, the study hopes to offer a thorough grasp of the variables that greatly affect the dynamics of pricing in the post-IPO era. | technical aspects continue to determine post-IPO performance. |
| **A5** | Han & Kim | 2021 | ANN–MLP | This study posits that multivariate regression models (MVMs) incorporating ANNs offer stronger explanatory power for post-listing stock values compared to simpler MVMs. The main objective is to examine whether utilizing ANNs, as opposed to employing a range of equally weighted and aggregated indicators, enhances the explanatory power of stock prices after listing. Furthermore, the study assumes that if the public offering price is less than the value determined by our model, then taking part in an IPO may increase the return on investment. | The MLP-ANN (Multilayer Perceptron Artificial Neural Network) exhibits enhanced predictive accuracy in estimating IPO listing prices when compared to a combination of diverse indicators with equal weights. |
| **A6** | Colak et al. | 2022 | XGBoost | To model the risk of an IPO failure by addressing the shortcomings of earlier research using conventional parametric approaches, which suffer from improper risk assessment because of the existence of several determinants. Hence, this study aims to consider thousands of determinants of IPO failure risk and model them through ML techniques. | The study's findings indicate that ML techniques provide superior estimations of IPO failure risk compared to traditional approaches, primarily due to their flexibility in handling a larger number of variables without restrictive assumptions. Through Gradient Boost modeling, the authors identify seven key variables, including the volatility of the firm's ROA and cash flows, the size of its accounts payable, pre-tax income to common equity, total short-term debt, and selected macroeconomic indicators. These variables emerge as the top predictors of IPO failure risk in the analysis. |
| **A7** | Baba & Sevil | 2020 | Breiman (2001) invented the approach known as random forest. | This study aims to expand on the research conducted by Quintana et al. (2017) by examining other markets and offering additional evidence supporting the | Random forest outperformed other approaches in every category of the comparison, according to the prediction findings. The IPO proceeds and |

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| | | | | advantages of utilizing random forest algorithms in predicting initial returns of IPOs. | IPO volume are the most important determinants of IPO first returns, according to the variable importance measure. |
| **A8** | Tao et al. | 2018 | Text analytics and predictive modeling using various ML algorithms, including ensemble models. | To assess how characteristics taken from forward-looking statements (FLS) and IPO valuation relate to one another. | The best results were that of LSTM, which was thus used as a classification model in the FLN classifier. The results of the study indicate that FLN features excel in predicting pre-IPO price revision as against post-IPO first-day returns. |
| **A9** | Verner & Rosocha | 2015 | Genetic algorithm (GA) and multi-layered feed-forward neural network. | To forecast yield spreads required in the main bond market through GAs based on ANNs. | Six learning algorithms were applied to the sample bond offerings, and the results were compared based on mean squared error and determination coefficient. The best results were obtained on the application of the Gradient Descent Algorithm. |
| **A10** | Basti et al. | 2015 | SVM and ANN | To use cutting-edge algorithms like decision trees, SVM, and neural networks to look into the possibility of underpricing in Borsa Istanbul listed businesses and determine what influences the first-day excess returns. | The short-term performance of Turkish companies' initial public offerings (IPOs) is influenced by a range of factors. These factors include underwriting methods, annual sales amounts, total assets turnover rates, market sentiment, IPO stock sales procedures, offer prices, debt ratio, and the number of shares sold. Collectively, these elements play a prominent role in shaping the short-term performance of Turkish IPOs. |
| **A11** | Reber et al. | 2005 | ANN with MLP, sensitivity analysis, and GA. | This paper undertakes a comparative analysis of three models: a conventional linear regression model commonly employed in the existing literature, a multilayer perceptron model utilizing the same set of explanatory variables as the regression model, and an enhanced multilayer perceptron model incorporating a broader range of explanatory variables. The objective of this comparison is to evaluate the respective performance and | The primary focus of this paper was to examine and compare the effectiveness of ordinary least-squares regression and neural network models in predicting the size of an IPO's first-day return. The key finding of this study indicates that a relatively simple neural network architecture incorporating seven input variables outperforms other models and is the preferred choice for accurate forecasting. |

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| | | | | efficacy of these models in capturing and explaining the underlying dynamics. | |
| **A12** | Yu & Huarng | 2013 | Multivariate model: Fuzzy time series and neural networks. | To support business owners in making decisions regarding the IPO's launch as well as helping them deal with the problem of market timing while making stock market investments. | The unique multivariate neural network model accurately predicts both positive and negative returns for the various indices with a 100% hit rate. Second, in terms of predicting the returns on all three stock indices, the suggested model performs better than pure neural networks and helps in wealth creation for entrepreneurial firms. |
| **A13** | Haefke & Helmenstein | 1996 | Multilayer feed-forward network (MLP) | To first predict ATX using both linear and neural network models and then predict IPOX one day ahead based on Observed ATX data. Finally, the aim is to make a comparison of the quality of this estimation based on Forecasted ATX values. | When compared to Buy and Hold or Simple Moving Average trading strategies, trading based on projections made based on neural network models greatly boosts an investor's profit. |
| **A14** | Haefke & Helmenstein | 1996 | Cointegration and Granger causality | To investigate times series properties of the IPO index and forecast the returns of Austrian IPOs using both linear and multilayer feedforward neural network error correction models. The objective is also to examine the profitability of various trading strategies to assess the economic value of the forecasts made. | The first result of this study highlights that ATX granger causes IPOX, whereas the opposite does not hold. The other finding is that neural network models outperform linear models, and hence market segment of IPOs in Austria can generate trading profits based on two-day ahead neural network forecasts. |
| **A15** | Kanas | 2001 | ANN | To build two stock return models–one non-linear and the other linear–and assess how well they forecast using the root mean squared error (RMSE) and forecast-encompassing methods (developed by Chong and Henry, 1984). | ANN forecasts indicate superiority in the analysis and confirm the existence of non-linear terms in the relationship between stock returns and fundamental variables. |
| **A16** | Robertson et al. | 1998 | OLS regression and multilayer feed-forward neural network. | To assess the accuracy of the neural network technique and OLS regression utilizing different predictor variables in order to forecast the initial return of an IPO in the US stock market. The goal is to construct three models: two will use neural networks, and one will use regression. The MAE method of error prediction is designed to be used for the comparison. | The MLP neural network gave the best results. The results show that the neural network model performs better than regression models as well as models created using Brainmaker. These models prove to be helpful for investors to predict the initial returns of IPOs before investing. |

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| **A17** | Esfahanipour et al. | 2016 | Tehran stock exchange using ANN and fuzzy regression. | The objective of this study is to, first of all, apply new methodologies to examine the effect of withdrawal probability on IPO underpricing and check whether it plays a role in affecting underpricing or not. Second, this analysis has been conducted on the Tehran stock exchange, and hence, the aspect of studying the effect has been done on an emerging economy. The possibility of offering withdrawal is thought to have an impact on underpricing. So, the goal is to forecast underpricing by comparing the outcomes of fuzzy regression, ANN, and normal regression. To examine if underpricing can be impacted by the offering's likelihood of withdrawal as well. | While forecasting ATX (the stock market index of Austria), the results of linear and ANN models are similar concerning the error measures taken; however, when it comes to forecasting IPOXatx, the ANN models perform better as they can capture the non-linear trend in ATX which helps them predict IPOXatx better. In other words, ANN outperforms the linear model in the case of the prediction of IPOXatx. |
| **A18** | Quintana et al. | 2017 | Random forest. | To evaluate and contrast the random forest technique's output with eight benchmark approaches, then use 10-fold cross-validation to choose the winner based on the RMSE. | For comparison, the results of the random forest technique were compared with eight ML algorithms, which are quite prominent, such as least median of squares regression, IBK, LWL, M5P, M5Rules, multilayer perceptron, radial basis neural networks, and SMO-regression. The results of the random forest technique were the most superior, followed by IBK, with LWL and MLP offering the worst results. Price came out to be the most significant predictive variable out of all. |
| **A19** | Luque et al. | 2012 | GA | This paper aims to introduce a GA-based tool that is useful for IPO underpricing prediction. | The GA used in the suggested rule system is based on a Michigan technique, which enables predictions to be made based on a set of identifying rules. The system creates certain rules that can be applied to patterns with comparable behavior. The method was tested using a sample of US IPOs and three distinct configurations of a 100-fold cross-validation analysis. The system yields extremely competitive outcomes. |
| **A20** | Kim et al. | 2019 | Rough set theory and GA. | The goal of this research is to create a machine-learning investment | This research uses ML algorithms to create investment strategies |

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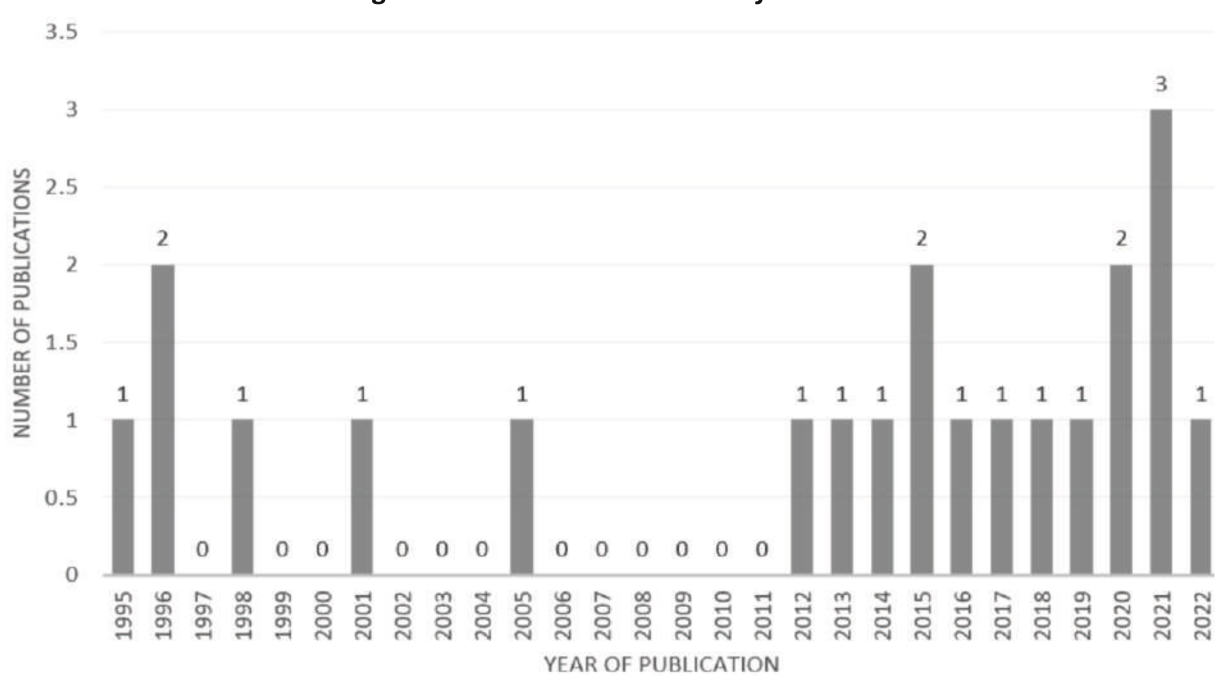
| | | | | strategy for IPOs and then assess how much the returns increase when employing this strategy in comparison to benchmarks. In other words, the aim is to see whether excess returns are possible using an ML strategy developed using rough set theory and GA algorithm as compared to simple investment in IPOs using public information. | and portfolios using GA rough set theory in order to guarantee continued economic growth as a result of increased financial market efficiency. The results gave a prediction accuracy of 63%, which decreased as the number of days between listing and target increased. Also, the port folios created using GA rough set theory gave excess returns of higher than 10% as compared to benchmarks. |
| **A21** | Reber | 2014 | Cascade neural networks. | This study's goal is to integrate a risk-neutral approach with a cascade neural network technique and compare the estimation accuracy to linear benchmark models, traditional neural networks, and risk-adjusted valuation approaches. | The estimations from the cascade neural network (Cascade) are more accurate than those from the MLP and the linear benchmark model (Linear). The cascade neural network performs better since it can account for varied interaction effects together with the nonlinear and linear functional forms. |

### *Year-on-Year Analysis of Publications*

**Figure 2.** ***Year-wise Publication of Articles***



## Discussion/Findings

The following findings have been noted following a comprehensive evaluation of the shortlisted studies' quality on IPO and ML approach utilizing the PRISMA flowchart.

To assess the suitability of the procedural component of the publications, a number of quality features were noted, and Table 1 gives an overview of the methodological quirks of the research that made the shortlist. As previously mentioned in Section 2.3, the research has been carried out using a variety of criteria that have been categorized as quality questions. The results of the seven assessment questions reveal that the range of all the studies lies between 3.5 and 7. However, there is only one study by Robertson et al. (1998) that satisfied all the parameters of quality assessment and obtained a score of 7. However, the ratio of the number of citations received over the years of publication of the study is only 0.63.

Table 1 (QA table) also reveals that a score of 1 has been allotted to all the studies for QA5, i.e., about the diagnosis of the model applied. It means that there has been an evaluation criterion to check the accuracy of the results obtained by the models applied in various studies. Mean squared error (MSE) and root mean squared error (RMSE) have been the two most common criteria to adjudge the accuracy of the prediction results of different techniques of IPO performance evaluation.

The research by Han and Kim (2021) received a zero for this criterion because it did not provide a sufficient justification for the inclusion of variables that were taken into consideration for the model, whereas the majority of studies received a score of 1. The criteria for including the relevant variables were only partially explained by three research, while the majority of publications clearly stated why they should be included, earning them a score of 1.

It was discovered that the majority of the studies had received low marks for clarity when it came to evaluating the model's application to a real-world scenario based on a vertical analysis of the studies' criteria. QA6 received a score of 0 or 0.5 because, in other words, few studies had used the procedure to explain the model's out-of-sample validation feature using test set data.

To analyze whether there is any relationship between the quality score given to each study as per of structured literature review method and the ratio of citations received by the article throughout its publication, the correlation has also been calculated. The results show a negative correlation of –0.16 between the two, thus highlighting that there may be an inverse relationship between the quality of the paper for the methodology applied and the number of citations received by the article concerning the time published. On the other hand, the SJR value of the journal in the year of publication of the article shows a positive correlation value of 0.38 with the quality score of the article. It indicated that a higher QA value of the article goes hand in hand with the SJR score of the journal in which it has been published. It is possible to deduce that whereas journal metrics exhibit a positive link with the same QA score, article metrics have an adverse relationship with it.

As far as the years of publication of the shortlisted studies are concerned, the graph (Figure 2) shows an increasing trend in the publication of articles on the performance evaluation of IPOs using ML techniques. The first article identified through the search matrix is that of Jain and Nag (1995), which was published in 1995, post which two articles were published in 1996. There were only three studies published on the said topic in the span of the next 15 years till 2013. Nevertheless, the graph indicates that one item will be published annually till 2020 after 2013 has passed. An increasing amount of research is being done on the use of non-traditional methods to forecast IPO listing prices, as seen by the numerous publications in the field of IPOs that have been published since 2020. In the year 2021, three articles were published, which is the maximum amount that can be done.

On screening the methodology used to analyze the performance of IPOs on the day of listing as well as post listing, the results indicate maximum application of the MLP model under the broad algorithm of ANN. Four studies have applied the technique of random forest, out of which two have used this algorithm in combination with other ML techniques. Furthermore, four research utilizing GA have been found; two of them used ANNs, one used rough set theory, and one study used GA independently. Additionally, XGBoost has been utilized for analysis in two other IPO-related studies. Other methods used in the publications that made the shortlist include the text analytics approach, fuzzy regression, cascade neural networks, and SVM.

The findings of the research using unconventional, non-linear approaches all point to the superiority of ML methods over conventional linear ones. When using ML techniques, the MSE is lower than when using linear techniques. The lack of assumptions and the limitations imposed by linear approaches on the number of variables that may be incorporated serves as a driving force behind the superiority of ML techniques over more conventional ones.

In the subject of IPOs, the application of emerging approaches such as XGBoost, rough set theory, text analytics, and GAs is highlighted by a study of the many types of ML algorithms used in the body of existing literature. At the same time, ANNs continue to be the most used algorithm.

## Conclusion

The research, which aimed to conduct a comprehensive analysis of the body of literature currently available in the field of initial public offerings concerning the use of ML techniques for performance evaluation both before and after listing, yielded some noteworthy results. A total of 21 studies that have been published since 1995 that are relevant to the subject under review were found using the SLR PRISMA approach. This emphasizes how little research has been done on IPOs that use AI methods for assessment. However, the increasing trend of publications in recent years reflects the emerging interest of researchers in the application of neural networks and other non-linear methodologies in the performance evaluation of IPOs. Seven quality assessment questions have been used to grade the current bank of identified literature according to the procedural application quality of the corresponding methodologies, with a particular emphasis on the ANN model's development. A score of 1 means that the quality requirements have been fully met for the purpose of creating an ANN architecture; a score of 0.5 means that the requirements have been partially met, and a score of 0 means that they have not been fully met.

| Study | Quality Score |
|---|---|
| Robertson et al. (1998) | 7 |
| Other studies (Average) | 5.5 – 6.5 |

Every study that assessed the model's accuracy by accurately diagnosing the forecasting error rate was given a score of 1 for that quality assurance criterion. However, the research does not clearly outline the process when it comes to formulating the model mathematically or figuring out how complex the model is in terms of how many layers, neurons, stop criteria, and iterations.

ML techniques have yielded higher results and improved prediction when compared to older methodologies. In addition to ANNs, a hybrid kind of ML techniques, including XGBoost, text analytics, rough set theory, and GA appear to be used. However, ANN proves to be the ML technology most frequently used to evaluate and predict underpricing in initial public offerings.

An overall picture of the state of the literature is given by the systematic review of research in the field of IPOs that apply ML approaches, emphasizing in detail the suitability of the procedural architecture of the models under discussion. Along with concluding that ML techniques, particularly ANNs, are superior, the paper also offers a glimpse of an emerging trend in AI modeling for IPO performance evaluation after listing and emphasizes the great potential for further research in this field to improve prediction accuracy and eliminate underpricing anomalies.

## Limitations of the Study and the Way Forward

While this study provides valuable insights into the application of ML techniques in evaluating IPOs, it is important to acknowledge its limitations. First, the review was confined to studies available in Scopus and Web of Science databases, potentially excluding relevant research from other sources. Furthermore, the primary emphasis on assessing ML methods may have obscured important discoveries from alternative methodological approaches.

Future research could explore a broader range of databases and methodologies to provide a more comprehensive understanding of IPO performance evaluation. Moreover, as the field of ML continues to evolve rapidly, future studies could delve deeper into the development of novel algorithms and hybrid models for more accurate IPO price prediction. Addressing these limitations will further enhance our understanding and application of ML in the context of IPOs. In the broader context, insights from Patanjali and Subramaniam (2019) underscored the pivotal role of government policies in fostering technological adoption and economic growth. This serves as a beacon for future research endeavors, aligning with our quest to enhance IPO evaluation methodologies.

## Authors' Contribution

Prof. Amit Kumar Singh was a vital supervisor and overseer of the study project. Prof. Singh helped to refine the study's methodology and ensure the validity of its analytical techniques because of his vast experience in finance and investment management, notably in the IPO market. Ms. Shivani Kalra assumed the primary role in the project's conception, data collecting, and in-depth analysis. The study benefited greatly from Ms. Kalra's guidance in stock markets and initial public offerings (IPOs), as she offered insightful advice on technique design and result interpretation. Ms. Kalra and Prof. Singh have worked closely together to perform ground-breaking machine learning-based research on IPO forecasting. Their combined knowledge and commitment have produced insightful discoveries that enhance our understanding of financial markets.

## Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

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## References

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. *Heliyon, 4*(11), e00938. https://doi.org/10.1016/j.heliyon.2018.e00938

Altman, E. I., Marco, G., & Varetto, F. (1994). Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience). *Journal of Banking & Finance, 18*(3), 505–529. https://doi.org/10.1016/0378-4266(94)90007-8

Baba, B., & Sevil, G. (2020). Predicting IPO initial returns using random forest. *Borsa Istanbul Review, 20*(1), 13–23. https://doi.org/10.1016/j.bir.2019.08.001

Basti, E., Kuzey, C., & Delen, D. (2015). Analyzing initial public offerings' short-term performance using decision trees and SVMs. *Decision Support Systems, 73*, 15–27. https://doi.org/10.1016/j.dss.2015.02.011

Breiman, L. (2001). Random forests. *Machine Learning, 45*, 5–32. https://doi.org/10.1023/A:1010933404324

Colak, G., Fu, M., & Hasan, I. (2022). On modeling IPO failure risk. *Economic Modelling, 109*, 105790. https://doi.org/10.1016/j.econmod.2022.105790

Colak, G., Fu, M., & Hasan, I. (2020). Why are some Chinese firms failing in the US capital markets? A machine learning approach. *Pacific-Basin Finance Journal, 61*, 101331. https://doi.org/10.1016/j.pacfin.2020.101331

Esfahanipour, A., Goodarzi, M., & Jahanbin, R. (2016). Analysis and forecasting of IPO underpricing. *Neural Computing and Applications, 27*(3), 651–658. https://doi.org/10.1007/s00521-015-1884-1

Füllbrunn, S., Neugebauer, T., & Nicklisch, A. (2020). Underpricing of initial public offerings in experimental asset markets. *Experimental Economics, 23*, 1002–1029. https://doi.org/10.1007/s10683-019-09638-7

Haefke, C., & Helmenstein, C. (1996). Forecasting Austrian IPOs: An application of linear and neural network error-correction models. *Journal of Forecasting, 15*(3), 237–251. https://doi.org/10.1002/(SICI)1099-131X(199604)15:3<237::AID-FOR621>3.0.CO;2-5

Han, J. J., & Kim, H.-J. (2021). Stock price prediction using multiple valuation methods based on artificial neural networks for KOSDAQ IPO companies. *Investment Analysts Journal, 50*(1), 17–31. https://doi.org/10.1080/10293523.2020.1870860

Jain, B. A., & Nag, B. N. (1995). Artificial neural network models for pricing initial public offerings. *Decision Sciences, 26*(3), 283–302. https://doi.org/10.1111/j.1540-5915.1995.tb01430.x

Kaastra, I., & Boyd, M. (1996). Designing a neural network for forecasting financial and economic time series. *Neurocomputing, 10*(3), 215–236. https://doi.org/10.1016/0925-2312(95)00039-9

Kanas, A. (2001). Neural network linear forecasts for stock returns. *International Journal of Finance & Economics, 6*(3), 245–254. https://doi.org/10.1002/ijfe.156

Khosla, R., & Tara, D. (2019). Artificial intelligence and robotics - Transforming the industrial economies. *Arthashastra Indian Journal of Economics & Research, 8*(5), 16–21. https://doi.org/10.17010/aijer/2019/v8i5/149679

Kim, J., Shin, S., Lee, H. S., & Oh, K. J. (2019). A machine learning portfolio allocation system for IPOs in Korean markets using GA-Rough set theory. *Sustainability, 11*(23), 1–15. https://ideas.repec.org/a/gam/jsusta/v11y2019i23p6803-d292597.html

Kitchenham, B. (2004). *Procedures for performing systematic reviews* (Keele University Technical Report TR/SE-0401). 1–28. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=29890a936639862f45cb9a987dd599dce9759bf5

Luque, C. E., Quintana, D., & Isasi, P. (2012). Predicting IPO underpricing with genetic algorithms. *International Journal of Artificial Intelligence, 8*(S12), 133–146. http://www.ceser.in/ceserp/index.php/ijai/article/view/2360

Nayak, D., & Barodawala, R. (2021). The impact of macroeconomic factors on the Indian stock market : An assessment. *Arthashastra Indian Journal of Economics & Research, 10*(2–3), 27–40. https://doi.org/10.17010/aijer/2021/v10i2-3/167172

Patanjali, S., & Subramaniam, D. (2019). India, the fourth industrial revolution, and government policy. *Arthashastra Indian Journal of Economics & Research, 8*(2), 32–44. https://doi.org/10.17010/aijer/2019/v8i2/145224

Quintana, D., Sáez, Y., & Isasi, P. (2017). Random forest prediction of IPO underpricing. *Applied Sciences, 7*(6), 636. https://doi.org/10.3390/app7060636

Reber, B. (2014). Estimating the risk–return profile of new venture investments using a risk-neutral framework and 'thick' models. *The European Journal of Finance, 20*(4), 341–360. https://doi.org/10.1080/1351847X.2012.708471

Reber, B., Berry, B., & Toms, S. (2005). Predicting mispricing of initial public offerings. *Intelligent Systems in Accounting, Finance, and Management, 13*(1), 41–59. https://doi.org/10.1002/isaf.253

Robertson, S. J., Golden, B. L., Runger, G. C., & Wasil, E. A. (1998). Neural network models for initial public offerings. *Neurocomputing, 18*(1–3), 165–182. https://doi.org/10.1016/S0925-2312(97)00077-5

Ross, G., Das, S., Sciro, D., & Raza, H. (2021). CapitalVX: A machine learning model for startup selection and exit prediction. *The Journal of Finance and Data Science, 7*, 94–114. https://doi.org/10.1016/j.jfds.2021.04.001

Singh, A. K., Jain, M. K., Jain, S., & Gupta, B. (2021). A new modus operandi for determining post-IPO pricing: Analysis of Indian IPOs using artificial neural networks. *Indian Journal of Finance, 15*(1), 8–22. https://doi.org/10.17010/ijf/2021/v15i1/157011

Tao, J., Deokar, A. V., & Deshmukh, A. (2018). Analysing forward-looking statements in initial public offering prospectuses: A text analytics approach. *Journal of Business Analytics, 1*(1), 54–70. https://doi.org/10.1080/2573234X.2018.1507604

Tealab, A. (2018). Time series forecasting using artificial neural networks methodologies: A systematic review. *Future Computing and Informatics Journal, 3*(2), 334–340. https://doi.org/10.1016/j.fcij.2018.10.003

Tkáč, M., & Verner, R. (2016). Artificial neural networks in business: Two decades of research. *Applied Soft Computing, 38*, 788–804. https://doi.org/10.1016/j.asoc.2015.09.040

Verner, R., & Rosocha, L. (2015). Yield spread prediction using a genetic neural network. *Investment Management and Financial Innovations, 12*(4-si), 192–199.

Yu, T., & Huarng, K.-H. (2013). Entrepreneurial firms' wealth creation via forecasting. *The Service Industries Journal, 33*(9–10), 833–845. https://doi.org/10.1080/02642069.2013.719893

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