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Behind the Rank: The Synthesis of a Causal Model of Variables Influencing Times Higher Education University Rankings

Sabar Aritonang Rajagukguk, Harjanto Prabowo, Agustinus Bandur and Rini Setiowati

Management Department, BINUS Business School Doctor of Research in Management, Bina Nusantara University, Jakarta, Indonesia 11480

sabar.aritonang@binus.ac.id, harprabowo@binus.edu, abandur@binus.edu, rsetiowati@binus.edu

Abstract. The purpose of this study is to investigate the causal relationships between performance indicators that determine a university's ranking, an area that has not been extensively researched despite its importance in shaping universities' reputations and attracting prospective students. We employed data-driven methods, specifically Non-combinatorial Optimization via Trace Exponential and Augmented lagRangian for Structure learning (NOTEARS) and Bayesian Networks, to analyze variables used in the Times Higher Education World University Rankings from 2011 to 2022. Our results demonstrate that research quality is the primary determinant of a university's ranking, with a substantial impact on other variables. This study contributes to both the theoretical understanding of university ranking systems and practical applications by suggesting that universities should focus on improving research activities to enhance their overall ranking.

Keywords: university reputation, university rankings, times higher education, causal modeling, bayesian networks

1. Introduction

The rise of university rankings since the early 1900s has led to a significant shift in global university governance, with institutions increasingly focusing on building and maintaining their reputations (Goldring, 2015; Morrissey, 2012; Welsh, 1982). Despite the various issues associated with global university rankings, such as isomorphism and the inability to measure the uniqueness of each university (Qureshi et al., 2021; Ringel et al., 2021), empirical evidence suggests that an institution's reputation significantly affects its performance (Beck et al., 2021; Dužević et al., 2017; Girdzijauskaitė et al., 2018; Morrissey, 2012).

For prospective students, university rankings are one of the primary considerations when choosing where to study (Grewal et al., 2008; Lubacz, 2022; Lukman et al., 2010; Quacquarelli Symonds, 2018). This consideration is based on the belief that higher-ranked universities will lead to more promising careers and better earnings (Cheong et al., 2019; Davis, 2016; Mekvabidze, 2020). This is also reinforced by the perception of companies that prefer alums from universities with higher rankings to be accepted into the workforce (Cheng et al., 2022; Cheong et al., 2019; Dong, 2021).

Prospective students, employers, and the labor market place considerable importance on university rankings, which in turn necessitates that universities strive for higher rankings (Mudzakkir et al., 2022; Puspitasari, 2009; Soutar et al., 2015). Previous studies have examined various factors influencing university rankings, including accreditation (Fernandes & Singh, 2021), research h-index (Huang, 2012), academic outcomes (N.K et al., 2018), citation levels (Hossain & Ahmed, 2020), and socioeconomic and cultural conditions of a country (Jabnoun, 2009). However, these studies have not explored the causal relationships between the variables assessed in university rankings based on longitudinal data. Moreover, they have not investigated how each of these indicators interacts with one another and how indirect improvements in one metric can impact another. This gap in research highlights the need for a more comprehensive understanding of the causal relationships between ranking variables.

The aim of this study is to explore the causal relationships between indicators that affect a university's ranking based on longitudinal institutional ranking data from the Times Higher Education (THE) from 2011–2022. By employing a data-driven causal modeling approach, this research seeks to contribute to the understanding of how ranking indicators interact with one another, ultimately providing valuable insights for universities to develop more effective strategies for improving their rankings. The central research question of this study is: What are the causal relationships between the variables assessed in university rankings, and how do these interactions influence a university's overall ranking?

2. Literature Review

2.1. University Rankings and Reputation

Since the 20th century, there has been a change in the nature of the market, which has also influenced how universities are managed. Initially, universities were focused on teaching and research activities; and the success of a university is measured through its ability to create thinkers that can further develop the community around them (Girdzijauskaitė et al., 2018; Miles et al., 2017; Ringel et al., 2021; Snellman, 2015). This paradigm has changed, to which university reputation has become the most decisive success factor, and university rankings are seen as the most capable of representing the university's reputation (Angulo-Ruiz et al., 2022; Kumar & Thakur, 2019; Urdari et al., 2017). The current rankings, however, are seen as having several weaknesses. It has not been able to capture the uniqueness of universities based on differences in socioeconomic conditions and the philosophy of each university (Hallinger, 2014; Madikizela-Madiya, 2022) and measure the impact of universities on the social life of society (Urdari et al., 2017). Several alternative approaches were proposed to rank universities (Hossain & Ahmed, 2020) in order to accommodate for those weaknesses. For example, the ranking of universities can be done by data mining from websites and Twitter (Girdzijauskaitė et al., 2018; McCoy et al., 2018) and the addition of ranking indicators that facilitate the uniqueness of each region where the university is located (Hauptman Komotar, 2020). Although the current way in which rankings are measured is considered imperfect (Doğan & Al, 2019), it is realized that the current approach is still the most appropriate (Fernandes & Singh, 2021).

2.2. Times Higher Education Rankings

Five separate indicators with different weightages are constructed and evaluated to create the THE university rankings, which include teaching (30%), research (30%), citations (30%), international outlook (7.5%), and industry income (2.5%). An evaluation of institutions' perceived prestige in teaching is used to evaluate half of the teaching indicator. The staff-to-student ratio, doctorate-to-bachelors ratio, academic-staff-doctorates ratio, and institutional income make up the remaining half (Times Higher Education, 2018).

As for the research indicator, the majority of research evaluations are surveys designed to gauge a university's standing among its contemporaries for excellence in research. Research income and the total number of publications are also taken into consideration. With data on the university's research, the citations indicator is calculated by averaging the number of times a work is cited. As a result, the citation metric is adjusted in relation to the overall number of articles that the institution's faculty has produced. The percentage of international personnel and students, as well as the volume of international cooperation, are used to gauge the international outlook. Lastly, the total earnings that an institution receives from the industry for its research are used to calculate its industry income (Times Higher Education, 2018).

2.3. Implementation of Bayesian Networks on University Rankings

Bayesian networks have been used in various studies related to university rankings (Malacina et al., 2022; Susha et al., 2019; Yakymenko et al., 2020). In itself, bayesian networks are represented in the form of a Directed Acyclic Graph (DAG) with nodes representing entities and edges showing the relationship between those entities (Kim & Jun, 2013; Wilson et al., 2016; Yakymenko et al., 2020). This approach is usually used to explore the causal relationship between variables whose theoretical causality has not been discovered through a data-driven approach (Yakymenko et al., 2020; Zheng et al., 2018). The underlying theorem used in Bayesian networks, Bayes' theorem, is based on the formula:

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)} \tag{1}$$

where *P(A)* is the probability of *A*, *P(B)* is the probability of *B* occurring, *P(B|A)* is the probability of *B* occurring given *A*, and *P(A|B)* is the probability of *A* occurring given *B* (posterior probability) (Kim & Jun, 2013; Wilson et al., 2016; Yakymenko et al., 2020; Zheng et al., 2018).

The availability of data in the digital era has made the implementation of Bayesian networks relevant to understanding the causal relationship behind the data (Mueller-Langer et al., 2020; Yakymenko et al., 2020; Zheng et al., 2018). In research on university rankings, Bayesian networks have been used to identify the most influential factors in determining a university's rankings in Ukraine (Yakymenko et al., 2020). In addition, it has also been used to analyze the competitiveness of universities based on their rankings using QS world university rankings data and, subsequently, the creation of prediction models based on these data (Estrada-real & Cantu-ortiz, 2022). However, previous research has not yet attempted to discover a causal relationship between university rankings variables in a longitudinal manner from THE rating agency.

This study uses the NOTEARS algorithm, which is based on the formulation of optimized Bayesian networks to discover causal relationships. This algorithm is used because it has the ability to find latent causal structures from data (Zheng et al., 2018). There have been many attempts by previous researchers to find the causal structure of the data (Kuleshov & Ermon, 2021), and a challenge faced by all these algorithms lies in the process of estimating the structure of the directed acyclic graph (DAG) (Zheng et al., 2018). The DAG search space is combinatorial, and the computational effort needed requires resources that scale super exponentially with node or variable growth (Zheng et al., 2018). Hence, the NOTEARS algorithm was used since the computation effort required increases cubically instead of exponentially. Also, its ease of implementation and its performance has been proven to outperform previous methods (Zheng et al., 2018).

3. Methodology

The methodology of this study includes several key steps, as illustrated in Fig. 1.

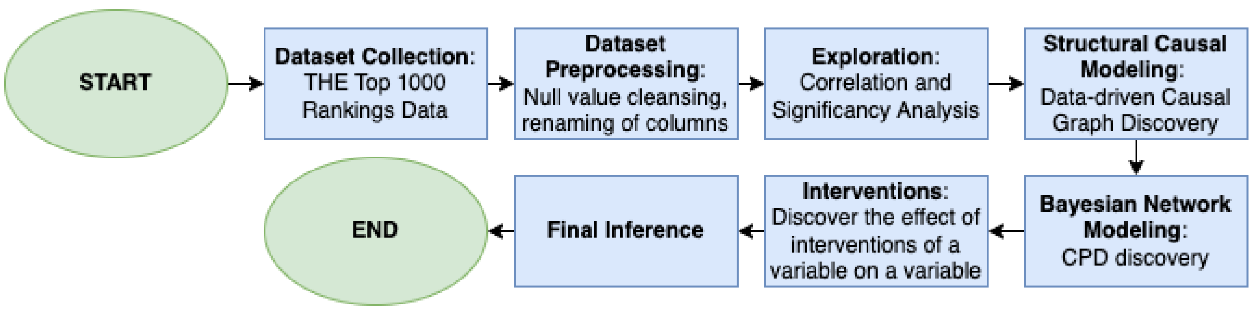

Fig. 1: Illustration of the proposed methodology.

The study commences with the collection of university ranking data from Times Higher Education (THE) via the Knoema dataset repository (Knoema, 2022). Subsequently, data preprocessing is conducted to ensure the use of clean data for analysis, which includes the elimination of data with empty values and the renaming of data columns for ease of further processing. The preprocessed data undergoes exploratory data analysis utilizing basic statistical methods, specifically Pearson's correlation coefficients between variables, to gain initial insights. The results of the initial exploration are then further analyzed through a structural causal modeling analysis using the NOTEARS algorithm to identify the causal relationships among variables and determine the causal structure of the data.

The causal structure identified in the previous step is utilized to construct a Bayesian network model to measure the conditional probability distribution of each variable and its relationship with other variables. The model is also used to conduct interventions to assess the effect of changes in one variable on others. All data preprocessing and analysis are performed programmatically using the Python programming language and various open-source libraries such as pandas 1.5.3, numpy 1.23.4, and causalnex 0.11.0.

4. Results and Discussion

4.1. Dataset

The dataset used in this study was obtained from the top 1000 university rankings provided by Times Higher Education (THE) globally from 2011 to 2022. The dataset comprises information pertaining to basic details of each university's institution, such as its name and location, rankings, scores in the five main ranking indicators, and student statistics from each institution. The dataset comprises a total of 8,080 data points. The description of each variable in the dataset is provided as follows (Times Higher Education, 2018):

- **Country**: The country where the university is located
- **University**: Name of university
- **Rank**: Rank of university
- **Teaching Score**: Quality of university teaching, measured by five performance indicators: reputation survey, staff-to-student ratio, the ratio of doctoral students to undergraduate students, number of doctorates awarded per academic staff, and institutional income
- **Research Score**: Quality of research, measured by the volume, quality, and reputation of the institution's research
- **Citations Score**: Research influence, measured by the number of times the work from academics in the university is cited
- **Industry Income Score**: The commercial impact of institutional research on the industry, mainly relevant to science, engineering, business, and technology subjects
- **International Outlook Score**: Relevancy of university both domestically and internationally, measured by international to domestic students and international to domestic staff ratio, as well as international research collaboration
- **Overall Score**: The average of the accumulated values of the previous five indicators
- **No. of FTE Students**: Number of full-time students
- **Student:Staff Ratio**: Student-to-staff ratio
- **International Students Percentage**: Percentage of international students
- **Share of Female Students**: Percentage of students who are women
- **Share of Male Students**: Percentage of students who are men
- **Time**: The year in which the rank was given

Preprocessing of the dataset was conducted to ensure that the data used was clean and appropriate for use in subsequent analysis. The distribution of data with empty values was visualized (see Fig. 2), and it was found that for certain variables, such as the overall score, only six thousand records were filled, while for others, there were several missing data points. These rows with incomplete values were removed. After the elimination of data with empty values, the number of remaining data to be processed was 6,062 rows.

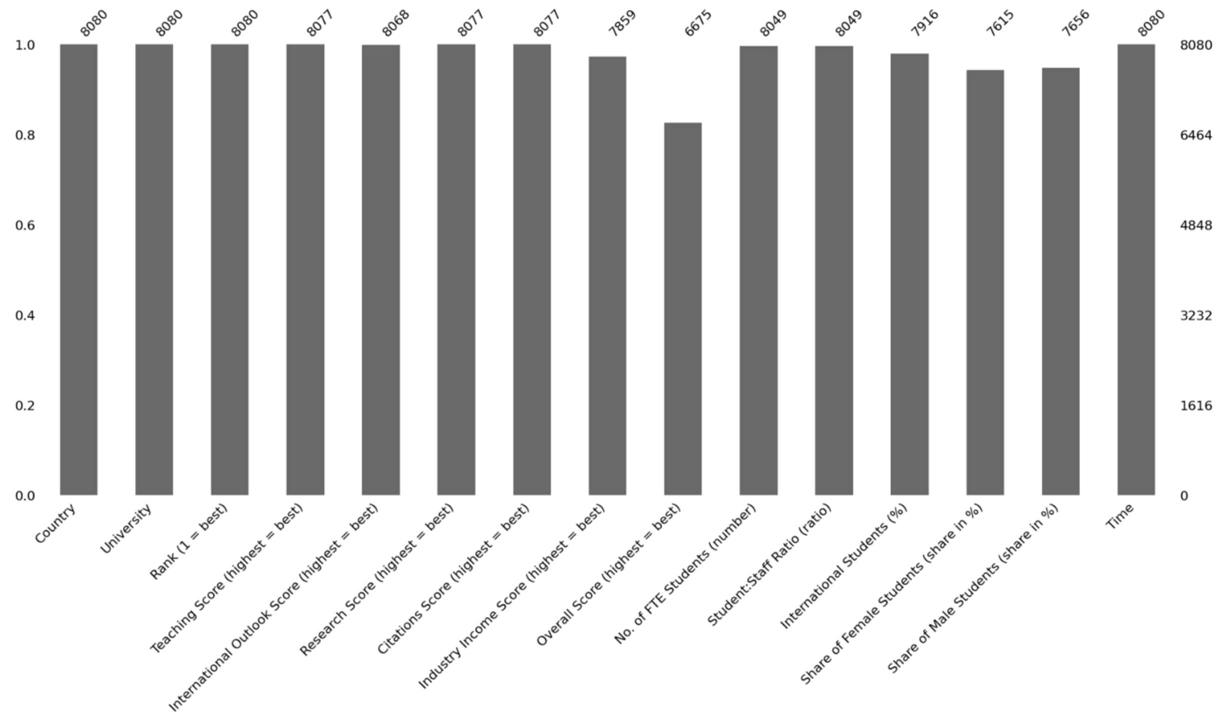

Fig. 2: Missing data distribution.

In addition to discarding data with empty values, the columns of the collected dataset were renamed to facilitate ease of processing later in programming. Some variables that would not be used in the analysis were also discarded. The columns were renamed to use solely lowercase, and whitespaces were replaced with underscores. Then, the country, university, time, and overall score variables were discarded. These variables were not used, considering that this study does not focus on exploring the causal relationship between university location and the time at which the ranking was given on university rankings. In addition, the overall score was also discarded because it is only the average accumulation of the five main ranking indicators and has also been represented by the rank variable.

Dataset exploration was first conducted by finding correlations between variables. It was found that some variables were highly correlated (>0.5, with a p-value significance of <0.05), indicating a strong relationship between the variables in this study (see Fig. 3 and 4).

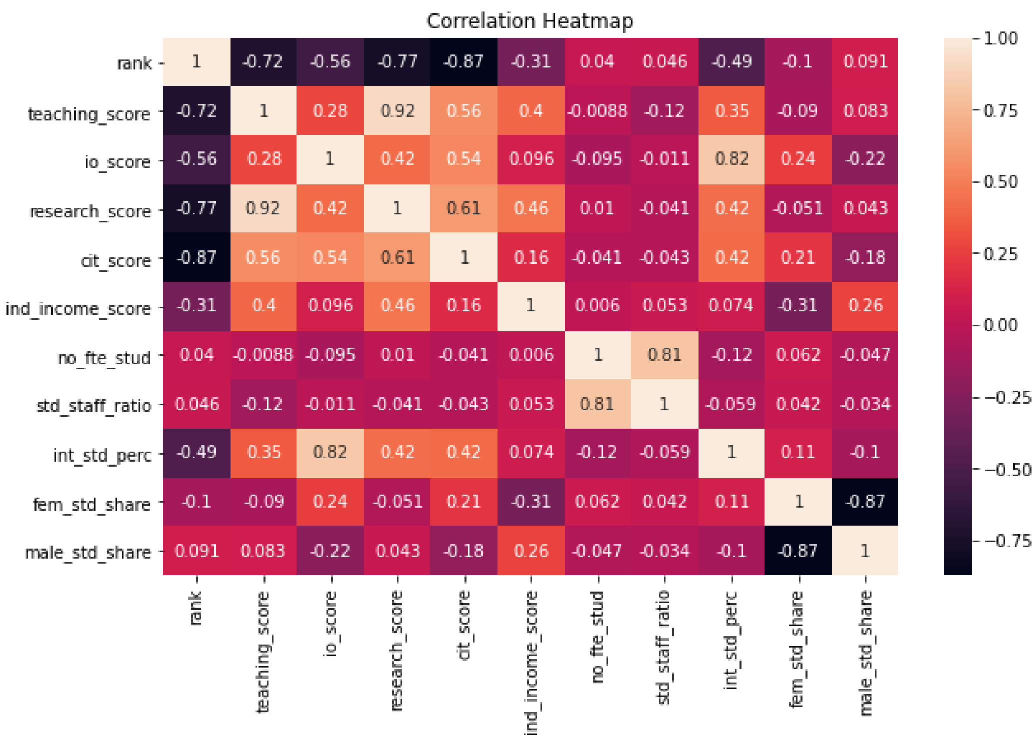

Fig. 3: Correlation heatmap of THE university ranking variables.

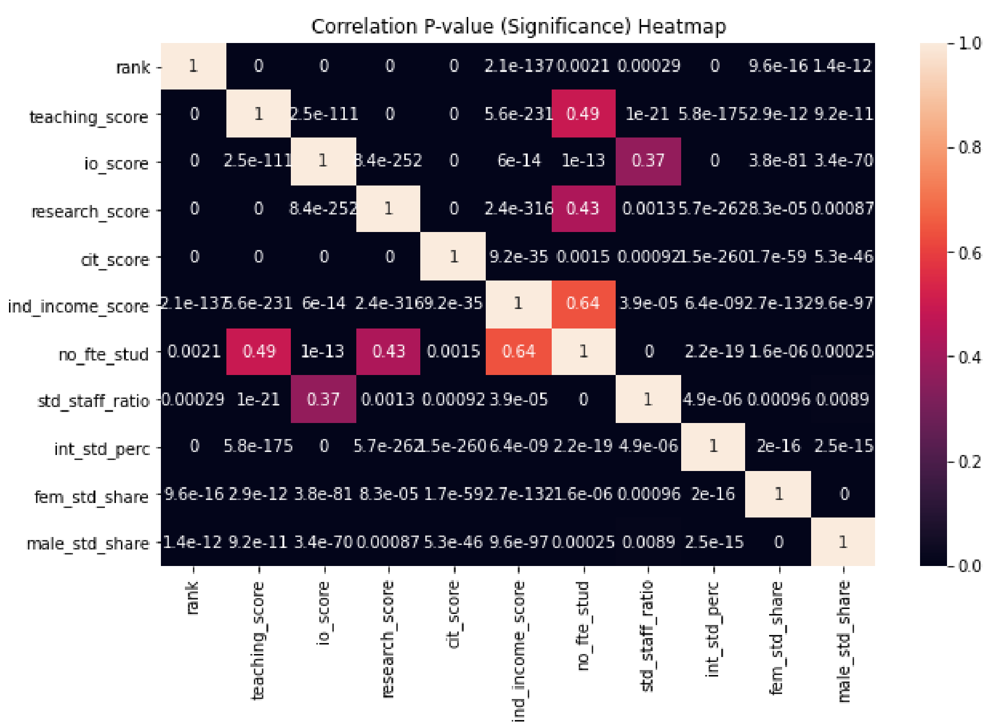

Fig. 4: Significance heatmap of variable correlations

Fig. 3 shows that there are several variables that are positively correlated, and some are negatively correlated. Almost all variables have a negative correlation with the rank variable; this is because the ranking value is inversely proportional, where the higher or better the university ranking, the smaller the ranking value. The variables with the most substantial relationship with university rankings were found to be the citation score, research score, teaching score, and international outlook score. On the other hand, the international student percentage has a moderate correlation with university rankings, with a coefficient value of -0.49, and the industrial income score has a coefficient value of -0.31. The number of full-time students, the percentage of male and female students, and the faculty-to-student ratio have very weak correlations with university rankings. Therefore, it can tentatively be inferred that the higher the citation score, research score, teaching score, international outlook, international student percentage, and industrial income score, the better the university's ranking will be. However, this will be confirmed later on as the direction of the relationship represented by the correlation coefficient is not clear.

Furthermore, it was found that the teaching score had a very strong positive relationship with the research score and citation score and a weak relationship with the industrial outlook score, international student percentage, and industry income score. Meanwhile, the teaching score actually has a very weak negative relationship (close to zero) with the number of students and the percentage of female students. It was also found that the international outlook score had the strongest relationship with the citation score. Another relationship found was between the research score and teaching and citation score, and the international outlook score with the international student percentage. This may indicate that improving the research score may help improve both the teaching and citation scores of a university and that the international outlook score of a university positively affects the number of international students enrolled. However, again, as the correlation coefficient is incapable of elaborating the directionality of the relationship, this will be further analyzed.

Some variables, such as the number of full-time students and student-to-staff ratio, have very weak or no correlation with other variables other than themselves. In addition, based on the correlation significance p-value heatmap, it can be seen that these two variables do not have a significant relationship with any other variable, suggesting that these variables have little to no impact on the university ranking; therefore, these two variables were removed from further analysis.

4.2. Structural Causal Analysis

After finding the correlation of each variable, the analysis was continued by finding the causal relationship between variables through causal modeling. The causal modeling approach used in this study is causal structure learning analysis using the NOTEARS algorithm. Before conducting the analysis, the data was first standardized because the scale of data for each variable (such as shares, percentages, and scores) differed. The standardization was done by subtracting the data mean and then scaling the data to the unit variance. After the scale of data was standardized, the data was then used with the NOTEARS algorithm to create a causal relationship structure graph (see Fig. 5).

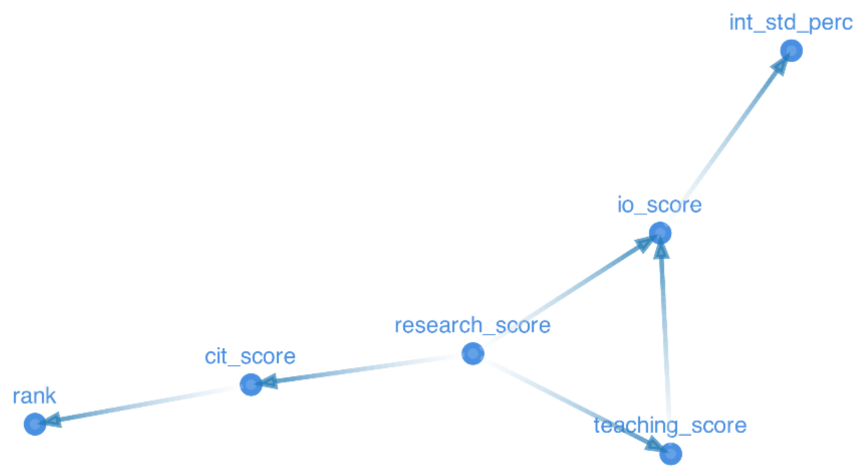

Fig. 5: Causal graph structure of THE university ranking variables

Significant findings from the causal model constructed using NOTEARS are illustrated in Fig. 5. First, the female student share, male student share, and industry income score variables have insignificant contribution effects on other variables. These variables, which did not have a significant effect, were excluded from the model visualization. Second, the research score, or the quality, volume, and productivity of good research, is the core antecedent of rank and international student percentage. The research score has a direct influence on the teaching score, citation score, and international outlook score, where those variables become mediator variables to ranking and international student percentage. Meanwhile, university rankings are solely directly influenced by the citation score and indirectly by the research score. Intuitively, the direction of causality from the research score to the teaching score variable may not make sense, as one would normally assume that high-quality faculty members would produce quality research. However, this relationship is actually in line with the statement released by THE regarding the teaching score:

"*The rankings are based on a strong belief that the quality of teaching at a university is itself predicated on the quality of its research: knowledge production and knowledge transfer at the university*." (Times Higher Education, 2018)

This is interesting because it indicates that a good teaching score does not necessarily help universities achieve good rankings or affect their research quality. However, if the quality of a university's research is good, the quality of teaching would also be good. Noting how universities need to become global universities that are accessible to all (Davis, 2016; Fernandes & Singh, 2021; Morrissey, 2012), this study shows that international student percentage is influenced by international outlook scores. These variables are indirectly influenced by the research score and teaching score.

4.3. Bayesian Network Modeling

Upon the establishment of the causal relationship model utilizing the dataset, a Bayesian network model was subsequently formulated to analyze the impact of each variable within the structure that had been established. It is to be noted that the library utilized for constructing the Bayesian network model only accommodates discrete values. Therefore, continuous variables, or those with an exorbitant number of potential values, were initially discretized into five distinct categories, namely very low, low, average, high, and very high, via the equal width binning method. Subsequently, after the data underwent further processing, it was employed to fit a Bayesian network model in order to chart the conditional probability distributions of each variable, and its relationship was inferred from the causal relationship model. Here, the conditional probability distribution represents the quantified value of the influence of a variable on other variables in the form of percentage probability. Based on the analysis, it was determined that the probability of a university's teaching score being classified as high, as a result of the university's research score being high, was 43%. The contribution of the research score to the teaching score is evident from the 62% probability of the teaching score being very high, given that the research score of the university was very high, and there was a 78% probability of the teaching score at a very low level if the research score was very low (see Fig. 6).

CPD of: teaching_score

research_score	Average	High	Low	Very High	Very Low
teaching_score					
Average	0.500000	0.529563	0.080700	0.012346	0.005609
High	0.022173	0.434447	0.000486	0.358025	0.000401
Low	0.475610	0.015424	0.638308	0.004115	0.207532
Very High	0.001109	0.017995	0.000486	0.621399	0.000401
Very Low	0.001109	0.002571	0.280019	0.004115	0.786058

Fig. 6: Conditional probability distribution of teaching score.

In furtherance of the analysis, it was discovered that the likelihood of a citation score being classified as very high, as a result of the research score of the university being very high, is 90% (see Fig. 7).

CPD of: cit_score

research_score	Average	High	Low	Very High	Very Low
cit_score					
Average	0.160754	0.110540	0.197375	0.008230	0.214744
High	0.390244	0.185090	0.371901	0.074074	0.147035
Low	0.042129	0.017995	0.134176	0.004115	0.290064
Very High	0.403548	0.668380	0.263977	0.909465	0.068510
Very Low	0.003326	0.017995	0.032572	0.004115	0.279647

Fig. 7: Conditional probability distribution of citation score.

Moreover, the probability that a university's ranking attains a very high status, given that its citation score is very high, is 83% (see Fig. 8).

CPD of: rank

cit_score	Average	High	Low	Very High	Very Low
rank					
Average	0.474382	0.164549	0.278203	0.016036	0.072165
High	0.188163	0.409149	0.045889	0.152021	0.002577
Low	0.174028	0.007624	0.367113	0.000641	0.207474
Very High	0.155477	0.418043	0.015296	0.830661	0.011598
Very Low	0.007951	0.000635	0.293499	0.000641	0.706186

Fig. 8: Conditional probability distribution of rank.

Furthermore, the probability of achieving a high international outlook score, given that the teaching score is average and the research score is high, was calculated. In that scenario, the likelihood of the international outlook score being very high is 35%. However, if the teaching score and research score are increased to a very high level, the probability of the international outlook score being very high decreases to 32% (see Fig. 9).

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CPD of: io_score
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research_score	Average					High					...	Very High					Very Low				
teaching_score	Average	High	Low	Very High	Very Low	Average	High	Low	Very High	Very Low	...	Average	High	Low	Very High	Very Low	Average	High	Low	Very High	Very Low
io_score																					
Average	0.314286	0.125000	0.272517	0.2	0.2	0.166667	0.254335	0.4	0.545455	0.2	...	0.142857	0.307692	0.2	0.283871	0.2	0.111111	0.2	0.189655	0.2	0.191760
High	0.160440	0.250000	0.286374	0.2	0.2	0.304762	0.202312	0.3	0.181818	0.2	...	0.428571	0.274725	0.2	0.354839	0.2	0.166667	0.2	0.082375	0.2	0.116480
Low	0.261538	0.375000	0.071594	0.2	0.2	0.147619	0.254335	0.1	0.090909	0.2	...	0.142857	0.109890	0.2	0.032258	0.2	0.333333	0.2	0.323755	0.2	0.347915
Very High	0.208791	0.166667	0.362587	0.2	0.2	0.352381	0.254335	0.1	0.090909	0.2	...	0.142857	0.296703	0.2	0.322581	0.2	0.055556	0.2	0.057471	0.2	0.055951
Very Low	0.054945	0.083333	0.006928	0.2	0.2	0.028571	0.034682	0.1	0.090909	0.2	...	0.142857	0.010989	0.2	0.006452	0.2	0.333333	0.2	0.346743	0.2	0.287894

Fig. 9: Conditional probability distribution of international outlook score.

Additionally, it was determined that the probability of the international student percentage being in the average category, given that an institution has a very high international outlook score, is 37%. This implies that globally esteemed universities do not necessarily have a large percentage of international students. However, if the international outlook score is very low, it was found that there is a 99% probability that the international student percentage is also very low (see Fig. 10).

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CPD of: int_std_perc
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io_score	Average	High	Low	Very High	Very Low
int_std_perc					
Average	0.008513	0.061694	0.001934	0.370071	0.001071
High	0.000655	0.003683	0.000645	0.042467	0.001071
Low	0.267191	0.638122	0.047066	0.553084	0.002141
Very High	0.000655	0.002762	0.000645	0.023256	0.001071
Very Low	0.722986	0.293738	0.949710	0.011122	0.994647

Fig. 10: Conditional probability distribution of international student percentage.

By evaluating the resulting conditional probability distribution values generated by the model, it can be inferred that the causal relationships of the previously constructed models are consistent with the current findings.

4.4. Intervention Analysis

The Bayesian network model constructed was further utilized to perform interventions, commonly known as counterfactual analysis, in order to uncover deeper insights. The probability computation performed during the intervention is based on the formula *P(Y|do(X))*, which can be interpreted as the probability distribution of Y, given that X has been manipulated to a specific value. The interventions carried out aimed to determine the probability of each variable attaining a very high category when another variable is set to a very high category (100% probability; refer to Table 1).

Table. 1: Comparison of probabilities pre- and post-intervention.

Intervened Variable	Variable	Previous Probabilities	After-intervention Probabilities
Research Score	**Rank**	**35,3%**	**78%**
	Citation Score	**25,5%**	**90,9%**
	International Outlook Score	**16,2%**	**31,0%**
	Teaching Score	**2,6%**	**62%**
	International Student Percentage	**0,4%**	**0,8%**
	Research Score	3,9%	100%
Teaching Score	Rank	35,3%	35,3%
	Citation Score	25,5%	25,5%
	International Outlook Score	**16,2%**	**19,7%**
	Teaching Score	2,6%	100%
	International Student Percentage	0,4%	0,5%
	Research Score	3,9%	3,9%
Citation Score	**Rank**	**35,3%**	**83,0%**
	Citation Score	25,5%	100%
	International Outlook Score	16,2%	16,2%
	Teaching Score	2,6%	2,6%
	International Student Percentage	0,4%	0,4%
	Research Score	3,9%	3,9%
International Outlook Score	Rank	35,3%	35,3%
	Citation Score	25,5%	25,5%
	International Outlook Score	16,2%	100%
	Teaching Score	2,6%	2,6%
	International Student Percentage	**0,4%**	**2%**
	Research Score	3,9%	3,9%

Table 1 lists the variables that were intervened, the probabilities of the variable being in the very high category before the intervention, and the resulting probability after the intervention. It was found that the most significant increase in probabilities resulted from an intervention in the research score. In particular, there was a significant increase in the probability of the rank, citation sore, teaching score, and international outlook score being very high. On the other hand, even though the probability of the teaching score being high was maximized, no effect was observed on the ranking and citation score.

The international outlook score had the largest change in probability. Comparing the effects of the probability maximization of the research score and teaching score, it is seen that the international outlook score is more influenced by the research score than the teaching score. Table 1 also shows that the probability of university rankings becoming very high is 83% if the probability of the citation score of universities becoming very high is 100%. Meanwhile, the intervention on international outlook score only increased the probability of the international student percentage by 1.6%. This suggests that the international student percentage can only be driven by an intervention on the international outlook score and, even then, only by a relatively small amount. Lastly, maximizing the value of the international outlook score does not affect the ranking, citation, teaching, and research score.

4.5. Discussion

The results of this study demonstrate a direct correlation between the research score and the citation score, teaching score, and international outlook score within the Times Higher Education (THE) university ranking system. The causal relationships between variables were analyzed, revealing two dependent variables: international student percentage and rank. The findings indicate that the citation score is the primary factor influencing university rankings, serving as a mediator for the effects of the research score on rank. This observation is consistent with previous studies that have identified a strong positive relationship between scholarly output and university rankings (N.K et al., 2018; Snellman, 2015).

This research contributes to the understanding of how research activities are the most influential factor in determining university rankings, contesting previous assumptions in the field of marketing management. Contrary to the belief that a university's global image (Dennis et al., 2016; Lee, 2019), student loyalty (Mallika Appuhamilage & Torii, 2019), student involvement in value co-creation (Díaz-Méndez et al., 2019; Quero et al., 2022; Sutarso et al., 2017), or teaching quality (Mudzakkir et al., 2022; Scott, 2021) are the primary determinants of university rankings, this study highlights the pivotal role of research activities.

Furthermore, these findings call into question the methodology of the THE ranking system, which asserts that the teaching score, research score, and citation score contribute equally (30% each) to university rankings (Times Higher Education, 2018). The data from this study suggests that the research score has the most substantial impact on university rankings. Moreover, the research score influences both teaching scores and international outlook scores, with a more robust effect on the former. This observation implies that efforts to improve teaching scores should prioritize the enhancement of research activities within the institution.

Practical implications of these findings for university administrators and policymakers include the strategic focus on strengthening research activities to indirectly influence university rankings, teaching quality, and global position. By investing in research infrastructure, fostering research collaborations, and promoting a research-driven culture, universities can potentially enhance their ranking, teaching quality, and global position in the long run. Such a shift in focus would require a reevaluation of resource allocation, faculty development programs, and institutional priorities to ensure that research activities receive adequate support.

In summary, this study challenges the methodology of the THE university ranking system, emphasizing the critical role of research activities in determining university rankings. By focusing on the enhancement of research activities, universities can potentially improve their rankings, teaching quality, and global position. This study's findings offer valuable insights for university administrators and policymakers in developing research-driven strategies to achieve better rankings and overall institutional performance.

5. Conclusion

In conclusion, the present study provides evidence that research score is a crucial determinant of university performance as measured by ranking, teaching score, international outlook score, and citation score. The results of this study suggest that universities should prioritize their research capabilities in order to improve their overall performance. However, it is important to note that this study has certain limitations, such as the use of data from only one ranking agency and limited sample size. Therefore, future research should aim to expand the scope and improve the methodology of the study to provide a more comprehensive understanding of the relationship between research scores and university performance. Additionally, it would be valuable to examine the internal strategies that universities employ to improve their research capabilities and to analyze data from multiple ranking agencies to provide a more holistic view of university performance.

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