

Assessment of Employment Prospects for Malaysia Graduates Using the Topsis Approach

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ABSTRACT

This study aims to analyse employment prospects for Malaysian graduates using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methodology, a multi-criteria decision-making tool. The increasing difficulty faced by graduates in securing employment highlights the necessity of a systematic evaluation of employability factors and an objective framework for assessing employment prospects. This research utilizes employment data from 2018 to 2022, examining critical variables such as industry demand, skill alignment, academic qualifications, and regional unemployment rates across Malaysia. By employing the TOPSIS method, the research ranks employment prospects in various sectors and states within Malaysia. The methodology provides a comparative assessment that considers the alignment of graduate skills with market needs, helping to identify gaps between academic training and employer expectations. This approach offers insights into the readiness of Malaysian graduates to enter the workforce and highlights disparities in job opportunities across regions.

The findings reveal notable differences in employment opportunities, with a strong emphasis on the importance of aligning academic qualifications with industry requirements. The study also underscores the role of higher education institutions in tailoring curricula to match labour market trends and fostering skill development relevant to employer needs. Furthermore, recommendations are provided for policymakers to design effective strategies that address regional employment disparities and enhance job creation. This research contributes significantly to understanding graduate employment trends by integrating quantitative data into a robust decision-making framework. It offers strategic recommendations for improving graduate employability, ensuring they are better equipped to meet the demands of the evolving job market in Malaysia.

Keywords: TOPSIS, Unemployment, Undergraduates, Pandemic

INTRODUCTION

In the era of fast changing technologies, digitization, and globalization are changing the shape of today's workplace. The technologies that barely existed until a decade ago are now continuously altering the jobs nature, patterns of work, and needed skills at present time. Technologies include AI, robotics, 3-D printing, Big Data, the Internet of things, Machine learning, Drone Technologies, nanotechnology, Renewable Energy Technologies, biotechnology increasingly are becoming mainstream in the workplace (Mainga et al., 2022). According to the International Labour Organisation, unemployment refers to individual who do not have a job but are actively seeking employment and preparing to accept employment within a time frame agreed upon by both the employer and the individual (Ahmad Aziz & Wagner Syed Mansoob Murshed, 2021). Youths aged 15 to 29 years represent a significant component of the national labour market, accounting for 40% of the total labour force (Ali, Che' Rus, Haron & Mohammad Hussain, 2018).

In recent times, there has been growing concern in society about the issue of college students struggling to find jobs. Organizations at all levels frequently focus heavily on employment, particularly the employment of recent college graduates. For recent graduates, the quality of their university education and personal growth are factors that influence employment opportunities. Currently, graduates of colleges contain certain issues that make finding a job challenging, like improper job placement and a lack of professional awareness. The difference between the supply and demand of talent in higher education and the market has led to four issues, schools finding it difficult to educate their students, companies finding it difficult to hire new employees, graduates finding it difficult to find jobs, and students finding it difficult to find appropriate positions, (Yujun et al., 2022). In the domains of management and decision science, the TOPSIS approach is extensively employed. In this paper, this method applied to standardize each attribute factor, find the positive and negative ideal solutions, calculate the distance between each decision-making scheme and the ideal solutions, and derive the relative benefits and drawbacks of each scheme. The multi-attribute decision-making problem can be successfully resolved by applying the TOPSIS approach, (Xiao Bo, 2023).

METHODOLOGY

A research design employing TOPSIS would clearly outline the research questions and goals, which typically focus on identifying the best option from a set of alternatives based on several factors. The design would then detail the methods used to collect data on how each alternative performs in relation to the established criteria. After data collection, the TOPSIS method would be applied to calculate how close each alternative is to an ideal scenario and a worst scenario. Finally, the design would specify how the TOPSIS results would be analyzed to identify the alternative that is closest to the ideal solution and therefore considered the optimal choice.

This study focuses on assessing employment prospects for undergraduate students in Malaysia. Defining a specific population frame for this research is challenging due to the vast number of students enrolled in universities across the country. Therefore, it will utilize data readily available from reliable sources like Malaysia's Department of Statistics (DOSM). This national level data provides a comprehensive overview of undergraduate programs offered by universities in Malaysia, along with relevant statistics such as enrolment figures. By analysing this data, it can gain valuable insights into the overall landscape of undergraduate education in the country.

Due to the extensive nature of the target population encompassing undergraduate students across Malaysia, this research will employ a secondary data analysis approach. Data collection will involve a systematic extraction and analysis of information from reliable sources, primarily focusing on the Department of Statistics Malaysia (DOSM) website. The DOSM website serves as a rich repository of data on various aspects of the nation, including education statistics. We will specifically target sections where data on undergraduate programs employed graduate employment graduate statistics. Additionally, reports and publications released by DOSM that provide insights into graduate employability and skills development in Malaysia will be valuable resources. By systematically extracting and analysing this secondary data, we can identify key factors influencing employment prospects for undergraduate students.

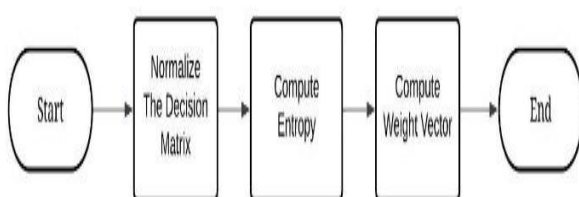


Figure 1: Flowchart method of Analysis Entropy Weight

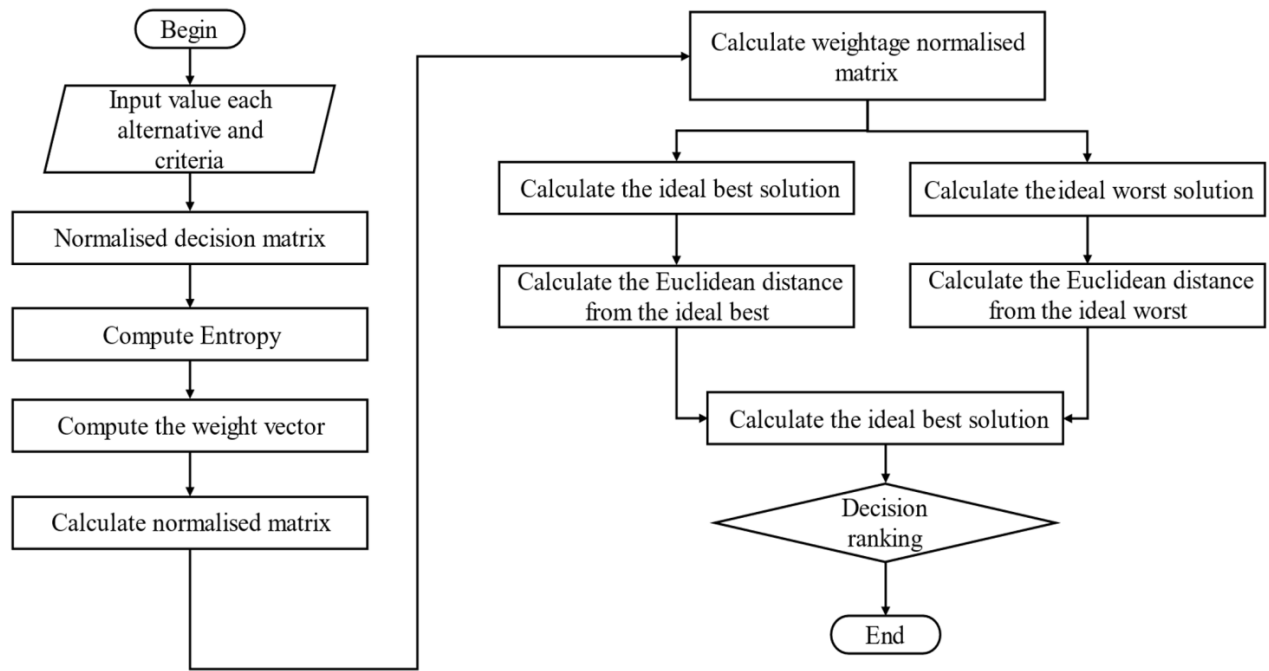


Figure 2: Flowchart Method of Analysis TOPSIS

According to the past researcher by (R. M. X. Wu et al., 2022) and (Elsayed et al., 2017) determining weights comes next after the assessment matrix is acquired. By computing the evaluation matrix, the entropy weight value and weights can be acquired directly. The following is the definition of the entropy of the i – th indicator for the evaluation matrix $R = (R_{ij})_{m \times n}$.

Step 1: Normalize decision matrix

$$R_{ij} = \frac{X_{ij}}{\sum_1^m X_{ij}}$$

Step 2: Compute Entropy

$$E_{ij} = -h \sum_{ij}^m R_{ij} \ln(R_{ij}), j = 1, 2, \dots, m$$

$$h = \frac{1}{\ln(m)}, \text{ where } m \text{ is the alternative}$$

Step 3: Compute The Weight Vector

The following defines the i – th indicator's entropy weight:

$$W_{ij} = \frac{1 - e_j}{\sum_{j=1}^i (1 - e_j)}, j = 1, 2, \dots, n$$

There are 6 steps to perform TOPSIS data analysis to obtain the weightage priority of the pairwise comparison matrix (Hoe et al., 2019).

Step 1: Formation of decision matrix $(x_{ij})_{m \times n}$:

Create the choice matrix and decide which criteria to include and how much weight to give each one. Create a ranking matrix indicated below:

$$(x_{ij})_{m \times n} = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1n} \\ X_{21} & X_{22} & \dots & X_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ X_{m1} & X_{m2} & \dots & X_{mn} \end{bmatrix}$$

Step 2. Calculate the normalized decision matrix.

In this phase, attributes can be transformed for easier comparison. The normalizing equations change widely. This study employed the normalization by sum method, which

$$r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^m X_{ij}^2}}$$

$$R = (r_{ij})_{m \times n} = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix}$$

Step 3. Determine the weighted normalized decision matrix.

The following formula is used to get the weighted normalized value:

$$T = (t_{ij})_{m \times n} = (w_j r_{ij})_{m \times n}, i = 1, 2, \dots, m$$

$$w_{ij} = \frac{W_{ij}}{\sqrt{\sum_{j=1}^n W_j}}$$

$$T = \begin{bmatrix} w_1 r_{11} & w_1 r_{12} & \dots & w_n r_{1n} \\ w_1 r_{21} & w_1 r_{22} & \dots & w_n r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 r_{m1} & w_1 r_{m2} & \dots & w_n r_{mn} \end{bmatrix}$$

Step 4. Calculate positive and negative ideal solutions.

Determine the measures of separation by using the n-dimensional Euclidean distance formula. The following represents how each option differs from the optimal solution:

$$A_b = \left\{ \left(\min(t_{ij} | i = 1, 2, \dots, m) | j \in J \right) / \left(\max(t_{ij} | i = 1, 2, \dots, m) | j \in J \right) \right\} = \{ t_{bj} | j = 1, 2, \dots, n \}$$

$$A_w = \left\{ \left(\max(t_{ij} | i = 1, 2, \dots, m) | j \in J \right) / \left(\min(t_{ij} | i = 1, 2, \dots, m) | j \in J \right) \right\} = \{ t_{wj} | j = 1, 2, \dots, n \}$$

Step 5. Calculate the relative closeness to the ideal solution.

As stated below, the alternative A_j 's relative proximity is determined by:

$$d_{ib} = \sqrt{\sum_m^n (t_{ij} - t_{bj})^2}, i = 1, 2, \dots, m$$

$$d_{iw} = \sqrt{\sum_m^n (t_{ij} - t_{wj})^2}, i = 1, 2, \dots, m$$

Step 6. Rank the preference order.

$$S_{iw} = \frac{d_{iw}}{d_{ib} + d_{iw}}, 0 \leq S_{iw} \leq 1, i = 1, 2, \dots, m$$

Step 7: Alternatives are calculated and ranked depending on their proximity to the ideal solution. Rank the alternatives according to s ($i = 1, 2, m$) S_{iw} = in descending order and select the alternative with the highest value of S_{iw} which is closest to 1.

Framework of T-test Two Sample in Equivalence Variance:

$$\text{Equal variance: } t = \frac{\mu_1 - \mu_2}{\sqrt{s_{2,p} \left(\frac{1}{n_1} + \frac{1}{n_2} \right)}}$$

$$\text{Pooled variance, calculated as: } S_{2,p} = \frac{(n_1 - 1)s_{2,1} + (n_2 - 1)s_{2,2}}{n_1 + n_2 - 2}$$

$$\text{Degrees of Freedom: } df = n_1 + n_2 - 2$$

Where:

μ_1, μ_2 are sample mean of groups 1 and group 2

n_1, n_2 are sample sizes of group 1 and 2

The first step for the two-sample t-test of equality of variances is to calculate the pooled standard deviation, representing the variance of both groups weighted by sample size. Then the second step is calculating the test statistic as a division of the difference between sample means by the standard error derived from the pooled standard deviation. This statistic is distributed as a t-distribution, with the degrees of freedom being the total number of observations in both groups minus two. The calculated t-statistics can be tested against a t-distribution based critical value to judge whether the mean difference between the two groups is statistically significant therefore one will be able to test the hypothesis (Xu et al., 2017).

RESULT & DISCUSSION

Table 1: Normalized Decision-Making Matrix

	Before Pandemic		After Pandemic		
State Year	2018	2019	2020	2021	2022
Johor	0.2735	0.2500	0.2449	0.2840	0.2744

Kedah	0.1446	0.1332	0.1426	0.1744	0.1688
Kelantan	0.1092	0.1054	0.1025	0.1243	0.1208
Melaka	0.0903	0.0898	0.0937	0.0971	0.0941
Negeri Sembilan	0.0950	0.0909	0.0948	0.1003	0.0977
Pahang	0.1049	0.1060	0.1091	0.1269	0.1221
Pulau Pinang	0.1839	0.1755	0.1802	0.1867	0.1809
Perak	0.1536	0.1528	0.1539	0.1799	0.1749
Perlis	0.0168	0.0179	0.0175	0.0198	0.0193
Selangor	0.8758	0.8909	0.8811	0.8521	0.8613
Terengganu	0.0856	0.0867	0.0769	0.0846	0.0823
Sabah	0.1672	0.1680	0.1876	0.1985	0.1928
Sarawak	0.1593	0.1572	0.1560	0.1622	0.1575
W.P Kuala Lumpur	0.2724	0.2290	0.2478	0.2864	0.2783
W.P Labuan	0.0072	0.0073	0.0069	0.0102	0.0099
W.P Putrajaya	0.0176	0.0158	0.0140	0.0137	0.0133

Table 2: Weighted Normalized Decision-Making Matrix

	Before Pandemic		After Pandemic		
State Year	2018	2019	2020	2021	2022
Johor	0.1313	0.1300	0.0784	0.0937	0.0988
Kedah	0.0694	0.0693	0.0456	0.0576	0.0608
Kelantan	0.0524	0.0548	0.0328	0.0410	0.0435
Melaka	0.0433	0.0467	0.0300	0.0320	0.0339
Negeri Sembilan	0.0456	0.0472	0.0303	0.0331	0.0352
Pahang	0.0503	0.0551	0.0349	0.0419	0.0440
Pulau Pinang	0.0883	0.0913	0.0577	0.0616	0.0651
Perak	0.0737	0.0795	0.0492	0.0594	0.0630
Perlis	0.0081	0.0093	0.0056	0.0065	0.0070
Selangor	0.4204	0.4633	0.2819	0.2812	0.3101

Terengganu	0.0411	0.0451	0.0246	0.0279	0.0296
Sabah	0.0802	0.0873	0.0600	0.0655	0.0694
Sarawak	0.0765	0.0818	0.0499	0.0535	0.0567
W.P Kuala Lumpur	0.1308	0.1191	0.0793	0.0945	0.1002
W.P Labuan	0.0035	0.0038	0.0022	0.0034	0.0036
W.P Putrajaya	0.0000	0.0082	0.0045	0.0045	0.0048

The (A_w) values determined by the TOPSIS model for the years before the pandemic (2018, 2019) and after the pandemic (2020, 2021, 2022) are 0.2414, 0.2327, 0.2819, 0.2812, and 0.3101, respectively. On the other hand, the (A_b) values for the same periods—2018, 2019, and after the pandemic in 2020, 2021, and 2022—are 0.002, 0.0023, 0.0022, 0.0034, and 0.0036, respectively. These best ideal (A_b) and worst ideal (A_w) solutions provide crucial benchmarks for evaluating performance over time. The results highlight changes in performance indicators, with values adjusted to reflect pre-pandemic and post-pandemic conditions. These findings serve as a reference for further optimization and improvement. Figure 3 and Figure 4 present the distance of all alternatives from the worst ideal solution (A_w) and the distance of all alternatives from the best ideal solution (A_b) respectively.

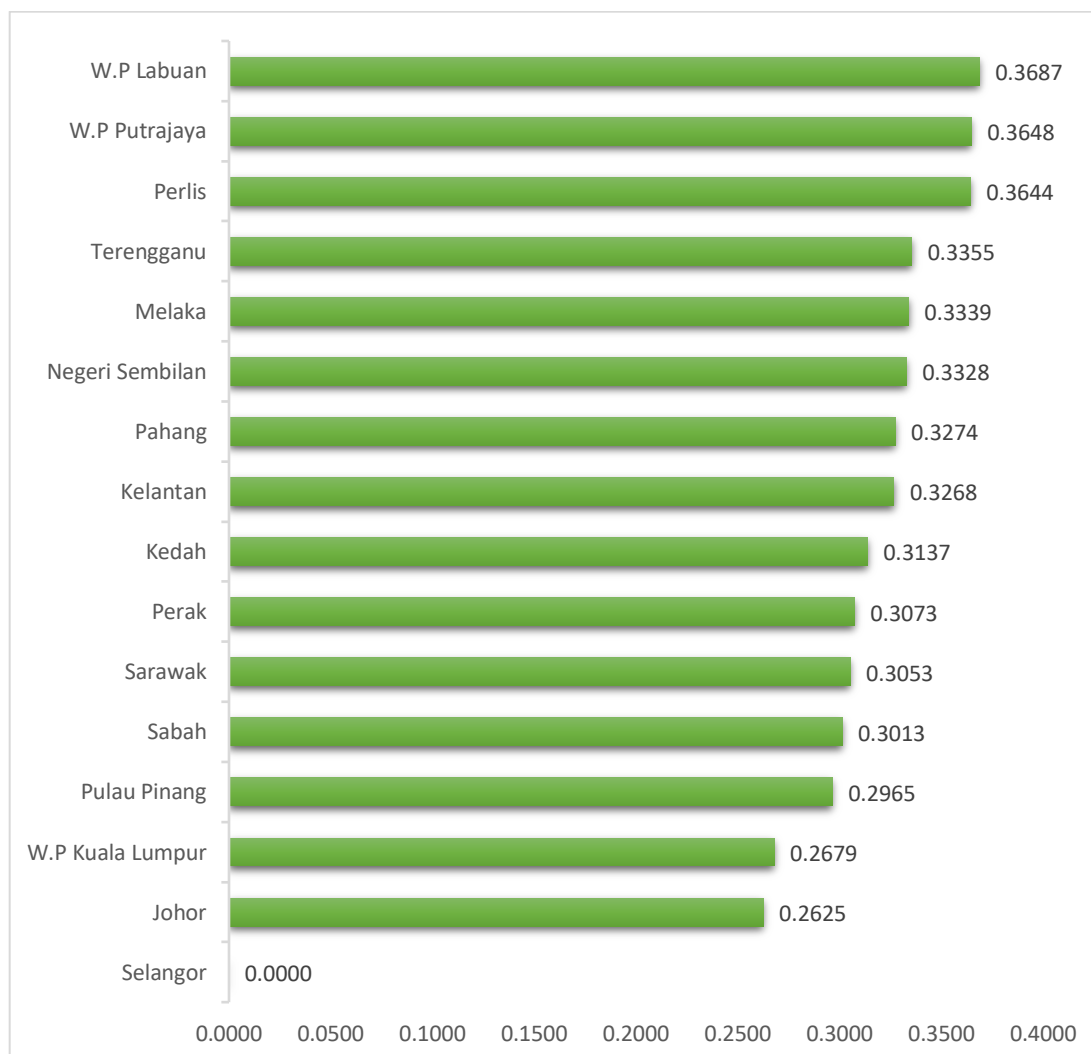


Figure 3: Distance of the alternatives from the worst ideal solution (A_w) before Covid-19.

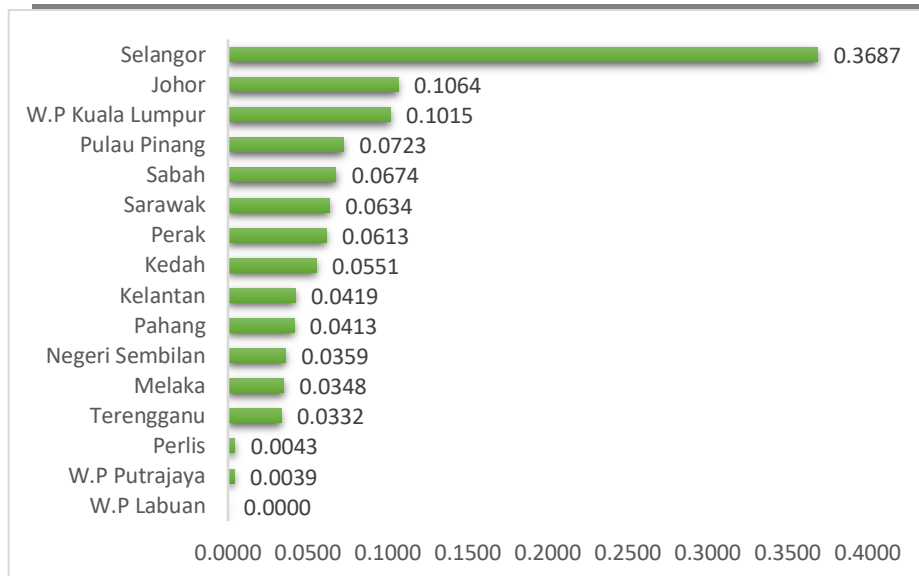


Figure 4: Distance of the alternatives to the best ideal solution (Ab) before pandemic Covid-19.

Figure 3 shows the distances of regions from the worst ideal solution (Aw) before the pandemic, in 2018 and 2019. WP Labuan had the highest (Aw) values, meaning it performed the furthest from the ideal solution. WP Putrajaya and Perlis also had high (Aw) values, indicating weaker performance. On the other hand, Selangor had the lowest (Aw) values in both years, showing it was the closest to the ideal solution and performed the best during this time. Figure 4 shows the distances of regions from the best ideal solution (Ab) for the same years. Selangor again had the smallest (Ab) values, proving it was the best-performing region. Meanwhile, WP Labuan had the highest (Ab) values, followed by WP Putrajaya and Perlis, showing they were further from the ideal performance. These results highlight Selangor's strong performance before the pandemic, while other regions like WP Labuan need more improvement.

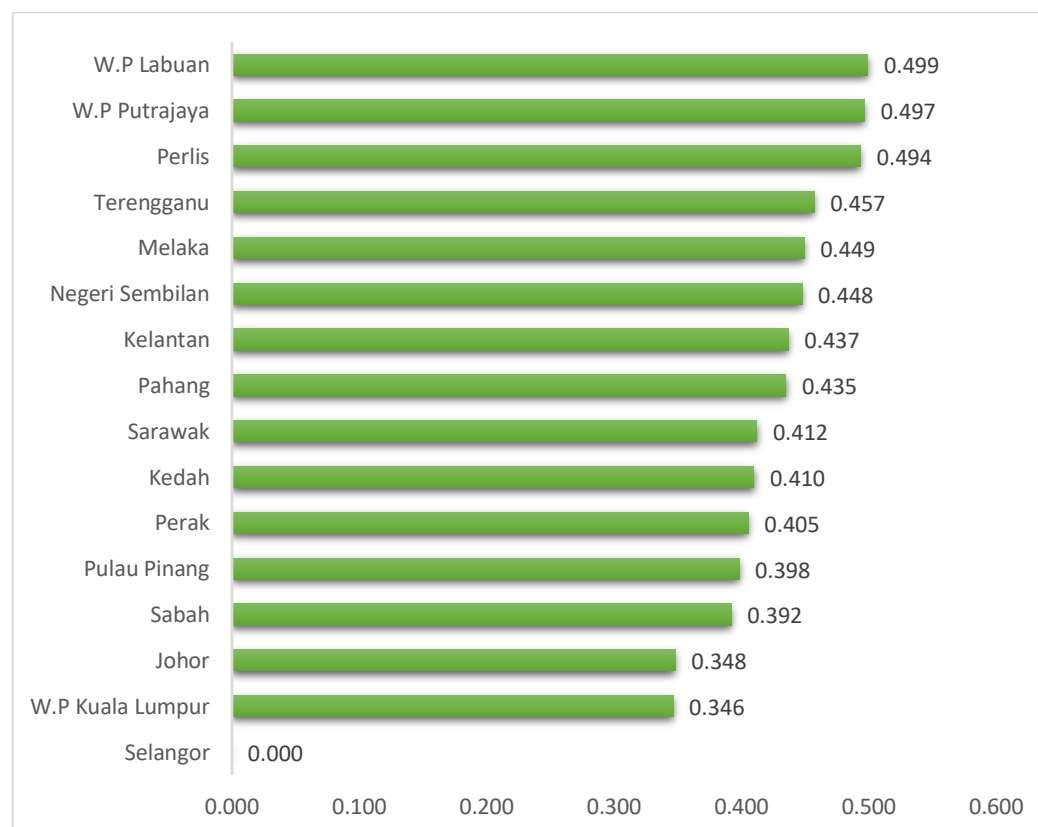


Figure 5: Distance of the alternatives from the worst ideal solution (Aw) after pandemic covid-19.

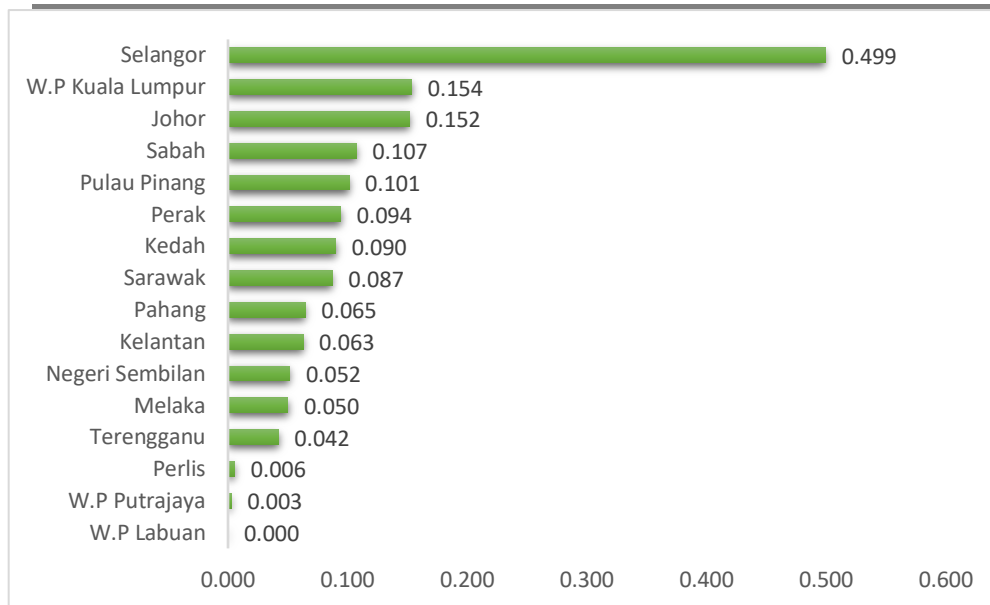


Figure 6: Distance of the alternatives from the best ideal solution (dib) after pandemic covid-19.

According to Figure 5 reveals compelling insights into the distances of the regions from the worst ideal solution (A_w) during the post-pandemic years of 2020, 2021, and 2022. WP Labuan persistently exhibited the greatest (A_w) values 0.499 in 2020, 0.497 in 2021, and 0.494 in 2022 indicating a pronounced deviation from optimal conditions and highlighting a need for substantial improvement. Similarly, WP Putrajaya and Perlis demonstrated high (A_w) values across the three years, reinforcing their position as regions with significant challenges. Conversely, Selangor consistently achieved the lowest (A_w) value of 0.000, reflecting its exceptional proximity to the ideal solution and underscoring its commendable performance throughout the post-pandemic period. Figure 6 further delineates the performance of the regions by showcasing their distances from the best ideal solution (A_b) for the same period. Selangor emerged as a consistent leader, achieving the smallest (A_b) values in 2020, 2021, and 2022, reaffirming its superior alignment with optimal performance standards. On the other hand, WP Labuan recorded the largest (A_b) values in all three years, signifying a stark deviation from the ideal benchmark and highlighting its need for strategic intervention. WP Putrajaya and Perlis also displayed relatively high (A_b) values, indicating room for further improvement. These findings serve as a testament to Selangor's sustained excellence while emphasizing the urgent need for performance enhancements in regions such as WP Labuan and WP Putrajaya.

Table 3: Relative Closeness to the Ideal Solution

State	Relative Closeness to the Ideal Solution, S_{iw}	Rank	State	Relative Closeness to the Ideal Solution, S_{iw}	Rank
W.P Labuan	1.0000	1	W.P Labuan	1.0000	1
W.P Putrajaya	0.9893	2	W.P Putrajaya	0.9944	2
Perlis	0.9883	3	Perlis	0.9885	3
Terengganu	0.9099	4	Terengganu	0.9155	4
Melaka	0.9057	5	Melaka	0.8997	5
Negeri Sembilan	0.9026	6	Negeri Sembilan	0.8965	6
Pahang	0.8880	7	Kelantan	0.8743	7

Kelantan	0.8862	8	Pahang	0.8706	8
Kedah	0.8507	9	Sarawak	0.8252	9
Perak	0.8336	10	Kedah	0.8200	10
Sarawak	0.8280	11	Perak	0.8115	11
Sabah	0.8172	12	Pulau Pinang	0.7973	12
Pulau Pinang	0.8040	13	Sabah	0.7850	13
W.P Kuala Lumpur	0.7253	14	Johor	0.6965	14
Johor	0.7116	15	W.P Kuala Lumpur	0.6929	15
Selangor	0.0000	16	Selangor	0.0000	16

Due to the COVID-19 pandemic, the interest in the gig economy is booming. Thousands of jobs are available in the gig platforms, which connect freelancers and employers worldwide. Thus, various initiatives have been provided by the government to support the growth of the gig economy. In relation to the COVID-19 pandemic, the labour market is not performing well. Even though there is a huge supply of labour, the demand for labour is interrupted. Besides, the world is changing towards the use of technologies to replace repeated tasks. Hence, the organizational factors are also interrupted. Therefore, to get employed, it lies on the shoulder of the job seekers themselves, whether to remain unemployed or to upgrade their skills. It goes to their personality, whether to be proactive or not in a challenging environment (Garin et al., 2023).

The results suggest that the slight difference in means between the periods before and after the pandemic is not statistically significant and may be attributed to random variation rather than any meaningful or systematic effect.

CONCLUSION

In conclusion, this study has provided an in-depth analysis of employment prospects for Malaysian graduates using the TOPSIS approach, highlighting critical patterns and factors influencing graduate employability from 2018 to 2019. The findings reveal that while certain fields of study align well with industry demands, others show significant gaps, leading to varied employment outcomes among graduates. Key determinants such as academic performance, field of study, and the relevance of skills to market needs play pivotal roles in shaping employment opportunities. The analysis underscores the importance of a strategic and data driven approach to addressing graduate unemployment, emphasizing the need for collaboration between academic institutions, industries, and policymakers. For further studies, it is suggested to use a bigger data set and vary the areas of educations in order to get better output and conclusion.

REFERENCES

1. Ahmad Aziz, M., & Wagner Syed Mansoob Murshed, N. (2021). The main determinants of unemployment in Afghanistan, and exploring the effects of insecurity and youth bulge in exacerbating the unemployment scenario.
2. Ain Mohd Zain, N., Syaiful Nizam Abu Hassan, M., Khairul Amri Kamarudin, M., & Hafis Amat Simin, M. (2024). Education And Challenges Affecting Sub-Urban Youth Involvement In Employment: A Case Study In Hulu Terengganu, Terengganu, Malaysia. *Educação E Desafios Que Afetam O Envolvimento De Jovens Suburbanos No Emprego: Um Estudo De Caso Em Hulu Terengganu, Terengganu, Malásia* (Vol. 16).
3. Bell, R. (2016). Unpacking the link between entrepreneurialism and employability: An assessment of the relationship between entrepreneurial attitudes and likelihood of graduate employment in a

- professional field. *Education and Training*, 58(1), 2–17.
4. Ciardiello, F., & Genovese, A. (2023). A comparison between TOPSIS and SAW methods. *Annals of Operations Research*, 325(2), 967–994.
5. Elsayed, E. A., Dawood, A. K. S., & Yan, K. (2017). Evaluating Alternatives through the Application of Topsis Method with Entropy Weight. *International Journal of Engineering Trends and Technology*, 46(2), 60–66.
6. Filippi, E., Bannò, M., & Trento, S. (2023). Automation technologies and their impact on employment: A review, synthesis and future research agenda. *Technological Forecasting and Social Change*, 191.
7. Garin, A., Jackson, E., Koustas, D. K., & Miller, A. (2023). The Evolution of Platform Gig Work. <https://www.irs.gov/pub/irs-soi/23rpevolutionofplatformgigwork>.
8. Godfrey, B., Maria, G. K., & Edith, G. M. M. (2021). Graduates Employability: Has the Expansion of the University Sector in Uganda improved Employment Prospects for Graduates? Employers and Lecturers Perspective. *International Journal of Educational Administration and Policy Studies*, 13(1), 66–71.
9. Hoe, L. W., Siew, L. W., & Fai, L. K. (2019). Performance analysis on telecommunication companies in Malaysia with TOPSIS model. *Indonesian Journal of Electrical Engineering and Computer Science*, 13(2), 744–751.
10. Junliang, W., Kaiyou, Y., & Zehan, S. (2020). Multi-grained rough set in job guidance for college graduates. *Proceedings - 2020 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery, CyberC 2020*, 268–271.
11. Lamrini, L., Abounaima, M. C., & Talibi Alaoui, M. (2023). New distributed-topsis approach for multi-criteria decision-making problems in a big data context. *Journal of Big Data*, 10(1).
12. Li, Y., Zhang, Y., Zhang, X., Zhao, J., Huang, Y., Wang, Z., & Yi, Y. (2024). Distribution of geothermal resources in Eryuan County based on entropy weight TOPSIS and AHP–TOPSIS methods. *Natural Gas Industry B*, 11(2), 213–226.
13. Liyin, L., Jianping, L., & Jie, T. (2023). Evaluation of Graduate Employment Ability Based on Ahp Entropy Weight Model. *2023 20th International Computer Conference on Wavelet Active Media Technology and Information Processing, ICCWAMTIP 2023*.
14. Madanchian, M., & Taherdoost, H. (2023). A comprehensive guide to the TOPSIS method for multi-criteria decision making. *Sustainable Social Development*, 1(1).
15. Mainga, W., Braynen, M. B. M., Moxey, R., & Quddus, S. A. (2022). Graduate Employability of Business Students. *Administrative Sciences*, 12(3).
16. Rahman, M., & Asadujjaman, M. (2021). Multi-criteria Decision Making for Job Selection. *2021 International Conference on Decision Aid Sciences and Application, DASA 2021*, 152–156.
17. Sun, Y., Zhu, H., & Xiong, H. (2023). Large-Scale Assessment of Labour Market Dynamics in China during the COVID-19 Pandemic.
18. Wu, R. M. X., Zhang, Z., Yan, W., Fan, J., Gou, J., Liu, B., Gide, E., Soar, J., Shen, B., Fazal-E-Hasan, S., Liu, Z., Zhang, P., Wang, P., Cui, X., Peng, Z., & Wang, Y. (2022). A comparative analysis of the principal component analysis and entropy weight methods to establish the indexing measurement. *PLoS ONE*, 17(1 January).
19. Wu, Z., & Li, Y. (2025). Multi-objective optimization of ventilation in pharmaceutical cleanrooms based on response surface methodology and AHP-entropy weight method. *Energy and Buildings*, 329.
20. Xu, M., Fralick, D., Zheng, J. Z., Wang, B., Tu, X. M., & Feng, C. (2017). The differences and similarities between two-sample t-test and paired t-test. *Shanghai Archives of Psychiatry*, 29(3), 184–188.
21. Yujun, Y., Yimei, Y., Wang, Z., Wei, L., Liyun, L., & Debin, H. (2022). Research on High-Quality Employment of College Students Based on Big Data Technology and Artificial Intelligence. *2022 19th International Computer Conference on Wavelet Active Media Technology and Information Processing, ICCWAMTIP 2022*. 596
22. Zheng, D. (2023). Simulation Research on College Students' Employment Prediction Model Based on Decision Tree Classification Algorithm. *Proceedings - 2023 International Conference on Internet of Things, Robotics and Distributed Computing, ICIRDC 2023*, 194–199.
23. Zhu, Y., Ma, J., Yang, X., Wang, Y., Li, H., & Wang, D. (2022). Research on the quality of graduate students in provincial universities based on entropy weight TOPSIS and RSR-take changchun

university as an example. Proceedings - 2022 18th International Conference on Computational Intelligence and Security, CIS 2022, 190–194.