

Graduates Employability Analysis using Classification Model: A Data Mining Approach

Maricris M. Usita

Occidental Mindoro State College, India
E-mail: maricrisusita954@gmail.com

Abstract

The employability of graduates serves as a measure of the success of every program offered within a Higher Education Institution. The employment assessment and evaluation of employment status allow improvement using data mining to analyze a vast amount of data in various areas. This study builds graduate's employment model using classification tasks in data mining, compares several data-mining approaches such as the Bayesian method and the Tree method with visualization, and explores the Association Rule using Apriori. The experiment used a classification task in Waikato Environment for Knowledge Analysis (WEKA) and compared the results of each algorithm, where several classification models were used. The experiment was conducted using accurate data sets from 1,489 graduate students for three years. The study provides valuable information about the graduate employment status, forecasting, visualization, and the exploration of classifiers algorithm to analyze the graduate employability in government, non-government organizations, self-employed, and unemployed. It is recommended to relate graduate employability to curriculum assessment and performance evaluation to identify measures and policies to improve students' performance.

Keywords— Bayesian method, Classification model, Data mining, Decision Tree

I. INTRODUCTION

Higher Education Institutions produce an increasing number of graduates every year. The employability of its graduates is vital for all academic institutions. Graduate tracer studies are essential for enhancing study program effectiveness in contemporary higher education [1]. It is one of the most significant factors reflecting educational programs and academic institutions' significance and relevance. The quality of acquired results is an essential part of higher education quality. [2]. Universities promote initiatives to improve their overall quality by encouraging graduates to work in industries. [3]. It provides helpful information to evaluate higher education results to enhance the quality of higher education institutions [4]. The institution provided the needed skills and competencies of graduates in line with their professional practice, and they were highly employable in a wide range of industries [5].

The employment status of graduates varies depending on their programs and field of specialization. Because of educational changes and the rise of disruptive technology, the demand in the workplace is fast-changing, emphasizing the importance of employability skills and literacy that will assure career success and degree program relevancy. [6]. In addition, to improve the production of high-level human resources that can spearhead efforts to attain national development [7]. The employed graduates are regular/permanent, working in the Philippines, finding their first job within 1 to 6 months, earning P 10,000.00 to P 20,000.00. According to the survey, their initial job level position is either professional, technical, or supervisory. [8].

The college uses the alumni tracers studies to assess the relevance of the curricula, knowledge, skills, and work values acquired by the graduates relevant to their employment;

identify the personal and professional characteristics, job placement, and school-related factors associated with their profession. In addition, it is used for quality assessment and tool for observation and formulation of feedback for professional development [9].

Hence, making career choices is complex since there are diverse factors affecting students' selection of programs when they enroll in higher education institutions [10]. Graduate tracer studies obtain intrinsic and extrinsic results and benefits if designed with rigor and inherent uniqueness. Tracer study methodologies provide simple and utilizable results that can consume appropriately at an individual and institutional level [11]. The conduct of a tracer study is a potent tool that documents the profile of graduates, which gives implications on the performance of graduates [12]. Therefore, it is vital to locate an excellent predictive model to determine the intervention suitable for particular graduate students to implement accurate predictions based on the identified problem.

The educational process has always been carried out based on development and market demands to meet standards [5]. Educational data is considered an indicator for predicting alumni students' employability status [13]. The conversion of raw data to create helpful information understood by different audiences is part of data mining. Educational data mining emerges as one tool to study academic data to identify patterns and help decision-making affecting education [14].

The application of data mining techniques improves the performance of my organizational domains and the concept applied in the education sectors for their performance evaluation and improvement [15]. Data mining techniques are used to determine the factors affecting graduates' employability [16]. The application of data mining algorithms helps the computer sciences retrieve information from the data in the form of hidden patterns even if the information is not directly stored in the database [17].

Classification is one of the more helpful techniques in data mining to create

classification models from an input data set. The decision tree and Naïve Bayes are part of the data classification [18].

The study explores the application of data mining to identify and improve the institution's services and enhance instruction. Analyzing patterns in large datasets can be efficiently analyzed with data mining techniques [15]. Employment prediction by the employability alignment of graduates is the primary goal of this paper. Significantly, the institution evaluates its performance in producing quality students. The paper helps the college have a data assessment of graduates to analyze and assess the program's outcome.

Likewise, gathering information about graduates is vital to assessing and improving institutional quality, monitoring employment outcomes, and enhancing the curriculum. Research studies used data mining techniques to extract rules and predict certain behaviors in several areas by identifying employees' performance as their productivity compared to their peers [19]. Therefore, applied classification techniques to search for graduate employability's essential element. The results were used to construct the graduate employability model and compare each model's accuracy under the Bayesian approach. Among the six different Bayesian methods, the results show that the AODEsr algorithm achieved the highest accuracy level of 98.3% [20].

The study reveals that work experience, occupation type, and times find work directly affect the employability of their graduates [19]. Every educational institution is mandated to trace its graduates to identify their current status, position, number of years in service, agency affiliation, etc. However, the Higher Education Institution (HEI) has no data analysis conducted to assess the current situation of their graduates within the industry. Therefore, there are no complete statistics on the profile of these graduates.

In addition, improving the quality of delivery is one of the biggest challenges of Educational institutions [21]. The employability of graduates is now an essential concern for students, both local and overseas. The research

paper is intended to support the higher education institutions in preparing the graduates with sufficient skills to enter the job market. Moreover, Occidental Mindoro State College is the home of the best graduates in the province. However, the graduates choose a course during their academic year but take a different path not aligned with the program they have studied for four years. Thus, there is a mismatch between their professional career and their course.

Graduate employment is one issue that needs to be given attention. A large number of graduates every year is accumulated; hence, obtaining their information on the whereabouts of the graduates can be a great help in the institution's strategic planning, particularly on the programs they offer. Furthermore, it is the institution's responsibility to craft students equipped on all aspects of their career growth and assist them in getting positions in their dream companies [21].

The paper provides necessary data on graduates' employability status, job environment, and the forecast on the job environment of the graduates. Furthermore, there were no further studies conducted on identifying what program within the college has a better performance based on the employment status of their graduates.

The researcher identified the fundamental causes of graduate employability using the Waikato Environment for Knowledge Analysis (WEKA) education domain. Specifically, this study aimed to: (1) determine the graduates' information in terms of gender and employment status; (2) Compare the employment trend per month; (3) Forecast the Graduate Employment Trends with seasonality and moving averages; (4) Visualize the Graduate Employment Trends; (5) Predict the Employment Rate using Classifiers and Trees Bayesian Network, and (6) Identify the Employment Pattern using Association Rule.

Conceptual Framework

The model is based on the concepts, theories, and findings of related literature, studies, and insights taken from them, as shown in Figure 1. The model combines the Cross-Industry

Standard Process for Data Mining [22] and Knowledge Discovery Process [23]. Data mining is worthwhile. It has five steps: business understanding, data understanding, data preparation, modeling, evaluation and deployment, and data discovery processes such as data cleaning, data integration, data selection, data transformation, data mining, evaluation, and presentation.

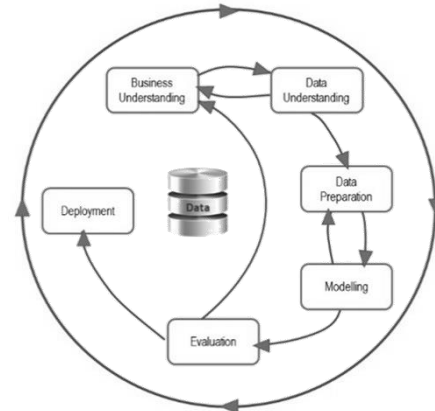


Fig. 1 Research Paradigm

II. METHODS

The model helps determine the potential attributes correlated significantly to graduates' target variables of employability. Figure 2 shows the Knowledge Discovery and Data Mining Process Model that the researcher underwent to accomplish the paper.

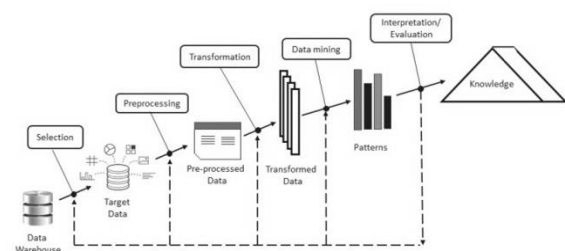


Fig. 2 Knowledge Discovery and Data Mining Process Model

Framework

According to Fayyad et al. (1996, the KD process) laid the foundation. Then, the KDD model was developed to support the complex and iterative knowledge generation process [24]. As shown in Figure 2, the KDD model comprises five steps from a data viewpoint: data selection and sampling, data processing, data transformation, data mining, and evaluation.

Data Selection

The data set needs to be analyzed from a large data store, and the selected data should be relevant to the knowledge discovery process.

Data Processing

The process involves dealing with noisy and missing data to ensure the correct input is used in the KDD process to generate valid output.

Data Transformation

The dimension reduction and transformation methods are used to identify functional attributes, which involves choosing the data mining task that matches the analysis goals, choosing an algorithm(s) and processes with corresponding parameters, and applying them to extract patterns from data.

Evaluation

The process interprets the mined patterns and extracts valuable knowledge to correct the subsequent iterations.

Instruments and Techniques

WEKA will be utilized for the classification and visualization of data sets.

Data Gathering Procedure

The study used standard google forms issued by the Monitoring and Evaluation unit of OMSC. It deployed the form to the students to gather information about their employment status from 2016 to 2018. Moreover, it also utilized secondary data available within the college.

Respondents of the Study

The graduate students under the College of Arts, Sciences, and Technology of Occidental Mindoro State College serve as the study's respondents. A total of 1,489 graduates from 2016 to 2018 thoroughly assessed graduates' employability situation.

III.RESULT AND DISCUSSION

The analytics solutions engaged for graduate tracer helps to understand fully the situation of graduates employed in different agencies, mainly if their work is related to the course they finished. Furthermore, this will predict if the graduates stay loyal to their companies.

Graduate Employed according to Gender and Employment Status.

Based on a percentage per Gender, for female graduates, 62% of which are employed, 31% are unemployed, and 7% are self-employed. On the other hand, 65% are used for male graduates, 27% are unemployed, and 8% are self-employed. Among 440 unemployed graduates, 323 are female, and 117 are male. In this illustration, male graduates have the lowest percentage of unemployed than female graduates, and it also comprises the highest employed rate than the female.

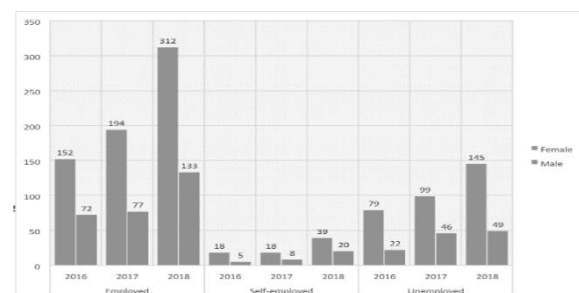


Fig 3. Graduate Employed from 2016 – 2018 according to Gender

Graduate Employment Trends per Month

Forecasting helps predict the future based on the available data incorporating appropriate processes, approaches, and models.

The OMSC Graduate Tracer forecasted the estimated number of employed, unemployed, and self-employed graduates. In addition, the graph contained data on the highest number of employed graduates during July within the period of 3 years because graduation takes place during April and graduates start to job hunt between May to June and most of the graduates get hired in July.

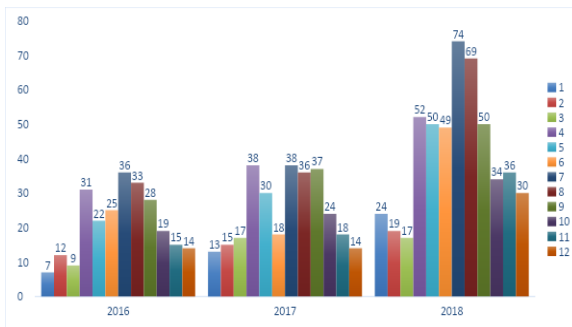


Fig. 4. Graduate Employment Trend per Month

Predicting Future Graduates Employment Trends

Forecasting helps predict the future based on the available data incorporating appropriate processes, approaches, and models. For example, the OMSC Graduate Tracer forecasted

the estimated number of graduates employed in the next coming year.

Time-Series Forecasting with Seasonality

Graduate trends may also provide patterns on cyclical and seasonal variations. The graduate tracer was able to determine trends and monthly patterns on employment. To forecast next year's number of employed and unemployed graduates, the number of occurrences by month within the three years from 2016-2018. Table 2 shows the future trend of employed graduates for the year 2019. The results obtained data for Employed (359), Self-employed (43), Unemployed (170) with an average of 190.

Table 1. Trends and Yearly seasonal forecast

Employment Status	2016	2017	2018	2019 FORECAST	Yearly Average	Yearly Factor
Employed	224	272	445	359	313.67	7.58
Self-Employed	23	26	59	43	36.00	0.87
Unemployed	101	145	194	170	146.67	3.55
Average	116.00	147.67	232.67	190	165.44	4.00
Total	348	443	698			
Grand Total	1489					
Overall Average	41.36					
2019 Forecast	190					

Table 2 shows the data on monthly trends of Employed Graduate from 2016-2018 and the month of July obtained the highest number of employments such as 36, 38, and 74,

respectively. The table also contains forecast data for 2019, and it shows that July obtained the highest with a value of 56. The data was also supported by a graph below.

Table 2. Trends and Monthly seasonal forecast

Month	2016	2017	2018	Monthly Average	Monthly Factor	2019 FORECAST
January	7	13	24	14.67	0.50	19
February	12	15	19	15.33	0.52	17
March	9	17	17	14.33	0.49	17
April	31	38	52	40.33	1.38	45
May	22	30	50	34.00	1.16	40
June	25	18	49	30.67	1.05	34
July	36	38	74	49.33	1.69	56
August	33	36	69	46.00	1.57	53
September	28	37	50	38.33	1.31	44

October	19	24	34	25.67	0.88	29
November	15	18	36	23.00	0.79	27
December	14	14	30	19.33	0.66	22
Average	20.92	24.83	42.00	29.25	1.00	33
Total	251	298	504			
Grand Total	1053					
Overall Average	29.25					
2019 Forecast	33					

The result of the abovementioned method is for forecasting for 2019 graduate employment rates as well as the monthly patterns are graphically presented in figure 5.

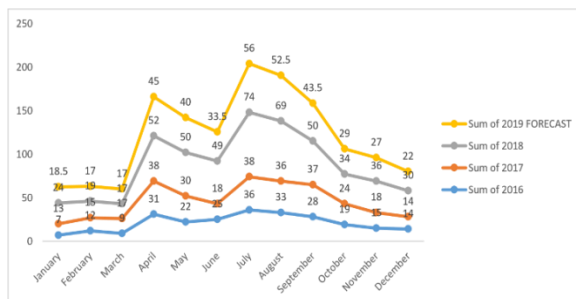


Fig. 5. Graduate Forecast for 2019, Trends, and Monthly Patterns

Forecasting using Moving Averages

The graph below shows the overall trends in a data set by calculating the moving average using a 2-period of data. The graduate employment forecasts presented cyclical and seasonal variations of the number of graduates employed.

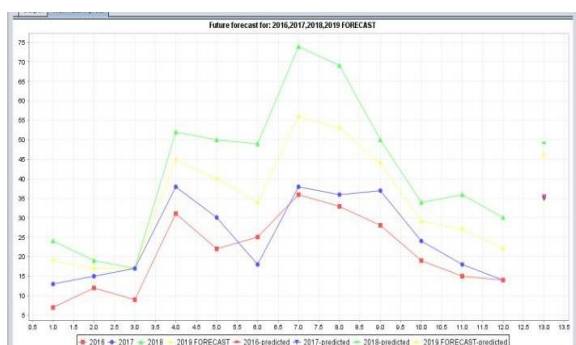


Fig. 6. Graduate Forecasts using 2 Point Moving Average

Visualization of Graduates Employment Trends

Figure 7 shows a visualization of the employment status of graduates with the program they finished and to their current employment. The results further explain that most IT graduates are unemployed while others are employed in non-government organizations.

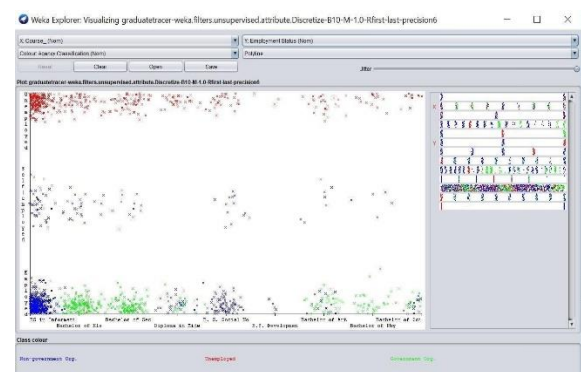


Fig. 7. Visualization of Employment Status with Program and the Agency of Graduates

Predicting Employment Rate using Classifiers and Trees Bayesian Network

Bayesian Network

Bayesian Network is used to take an event that occurred and predict the likelihood that any of the several possible known causes was the contributing factor and model sequences of variables.

The program and specialization of graduates are related to their current job status. Using the Bayes Net Classifier in Weka, occupation can be classified as permanent, temporary, contractual, self-employed, and unemployed. Using the training set in Figure 8, the model correctly classified instances with a 73.6064% accuracy rate, with a mean absolute error of

0.1256. Therefore, this model is accurate enough to predict the employment rate.

```

LogScore: Newu -10764.34704162554
LogScore: MLL -10767.47450039105
LogScore: EXIMOPR -10040.5543767044
LogScore: AIC: -10239.5543767044

Time taken to build model: 0.13 seconds

=== Stratified cross-validation ===
=== Summary ===
Correctly Classified Instances      1096      75.4054 %
Incorrectly Classified Instances    359      24.5946 %
Kappa statistic                    0.4543
Mean absolute error                0.1256
Root mean squared error            0.2672
Relative absolute error            41.077 %
Root relative squared error        68.357 %
Total Number of Instances         1459

=== Detailed Accuracy By Class ===
      TP Rate  PP Rate  Precision  Recall  F-Measure  MCC  ROC Area  PRC Area  Class
0.455  0.152  0.500  0.455  0.475  0.515  0.793  0.532  Temporary
0.476  0.078  0.454  0.476  0.480  0.464  0.464  0.615  Permanent
1.000  0.000  1.000  1.000  1.000  1.000  1.000  1.000  Self-employed
1.000  0.000  0.992  1.000  0.991  0.987  1.000  1.000  Unemployed
0.757  0.106  0.709  0.757  0.732  0.637  0.915  0.674  Contractual
Weighted Avg. 0.736  0.077  0.730  0.736  0.732  0.637  0.910  0.725

=== Confusion Matrix ===
  a b c d e <-- classified as
170 91 0 4 102 1 a = Temporary
  0 0 108 0 0 1 b = Permanent
  0 0 0 440 0 1 c = Self-employed
  0 0 0 0 257 1 d = Unemployed
  0 0 0 0 0 257 1 e = Contractual

```

Fig. 8. Bayes Network Model (Bayes Net) to Classify Employment Status

IV. DECISION TREE

The decision tree serves as a decision support tool that models the possible consequences and event outcomes. Figure 9 shows the model correctly classified instances with an accuracy rate of 75.7555% with a mean absolute error of 0.1202. The J48 has been used to test the possibility of the employment rate.

```

Number of Leaves : 23
Size of the tree : 29

Time taken to build model: 0.21 seconds

=== Stratified cross-validation ===
=== Summary ===
Correctly Classified Instances      1120      75.7555 %
Incorrectly Classified Instances    361      24.2445 %
Kappa statistic                    0.4908
Mean absolute error                0.1202
Root mean squared error            0.2491
Relative absolute error            39.2235 %
Root relative squared error        63.1197 %
Total Number of Instances         1459

=== Detailed Accuracy By Class ===
      TP Rate  PP Rate  Precision  Recall  F-Measure  MCC  ROC Area  PRC Area  Class
0.493  0.128  0.540  0.493  0.524  0.581  0.928  0.540  Temporary
0.514  0.061  0.432  0.514  0.364  0.291  0.874  0.409  Permanent
1.000  0.000  1.000  1.000  1.000  1.000  1.000  1.000  Self-employed
1.000  0.000  1.000  1.000  1.000  1.000  1.000  1.000  Unemployed
0.559  0.124  0.709  0.559  0.709  0.715  0.907  0.694  Contractual
Weighted Avg. 0.755  0.072  0.743  0.758  0.746  0.652  0.916  0.737

=== Confusion Matrix ===
  a b c d e <-- classified as
183 69 0 0 119 1 a = Temporary
112 60 0 0 19 1 b = Permanent
  0 0 108 0 0 1 c = Self-employed
  0 0 0 440 0 1 d = Unemployed
  0 0 0 0 257 1 e = Contractual

```

Fig. 9. Decision Tree Model (j48) Model to Classify Employment Status

Employment Pattern using Association Rule

Table 3 shows the comparison of two models used to determine which produces more accurate prediction based on the number of correctly classified values, incorrectly classified values, accuracy rate, and the mean absolute error. Based on the results, J48 obtained a high accuracy of 75.76% and a mean absolute error of .1202.

Table 3. Comparison of Bayes Net and J48 Model

Classifiers	Correctly Classified	Incorrectly Classified	Accuracy	Mean Absolute Error
Bayes Net	1096	393	73.61%	.1256
J48	1128	361	75.76%	.1202

Predictive Apriori Algorithm

This algorithm used more extensive support, traded with higher confidence, and calculated the expected accuracy in the Bayesian framework [25]. The results maximize the desired accuracy for future association rules data and generate association rules as the anticipated number of regulations by the user.

In this case, the Apriori algorithm has been tested to determine the patterns of employment rate. This algorithm generates frequent employment patterns by finding annotations that frequently occur. In addition, this method scans the dataset to collect all item sets that satisfy predefined minimum support. The best rule is shown in figure 10.

```

Database: EmploymentStatus
Attribute: 'Status of Appointment' {Temporary,Permanent,Self-employed,Unemployed,Contractual}

Data

Associator Model
Apriori
=====
Minimum support: 0.25 (372 instances)
Minimum metric confidence: 0.9
Number of cycles performed: 19
Generated set of large itemsets:

Size of set of large itemsets L(1): 12
Size of set of large itemsets L(2): 15
Size of set of large itemsets L(3): 6
Size of set of large itemsets L(4): 1

Best rules found:
1. AgencyClassification=Unemployed 440 ==> AgencyClassification=Unemployed 440 <conf(11)> lift:(3.32) lev:(0.21) [333] conv:(113.21)
2. AgencyClassification=Unemployed 440 ==> AgencyClassification=Unemployed 440 <conf(11)> lift:(3.32) lev:(0.21) [333] conv:(113.21)
3. EmploymentStatus=Unemployed 440 ==> AgencyClassification=Unemployed 440 <conf(11)> lift:(3.32) lev:(0.21) [337] conv:(107.62)
4. Status of Appointment=Unemployed 440 ==> AgencyClassification=Unemployed 440 <conf(11)> lift:(3.32) lev:(0.21) [337] conv:(107.62)
5. EmploymentStatus=Unemployed 440 ==> AgencyClassification=Unemployed 440 <conf(11)> lift:(3.32) lev:(0.21) [337] conv:(107.62)
6. Status of Appointment=Unemployed 440 ==> AgencyClassification=Unemployed 440 <conf(11)> lift:(3.32) lev:(0.21) [337] conv:(107.62)
7. Status of Appointment=Unemployed 440 ==> EmploymentStatus=Unemployed 440 <conf(11)> lift:(3.32) lev:(0.21) [339] conv:(105.96)
8. EmploymentStatus=Unemployed 440 ==> Status of Appointment=Unemployed 440 <conf(11)> lift:(3.32) lev:(0.21) [339] conv:(105.96)
9. AgencyClassification=Unemployed EmploymentStatus=Unemployed 440 ==> AgencyClassification=Unemployed 440 <conf(11)> lift:(3.32) lev:(0.21) [337] conv:(107.62)
10. AgencyClassification=Unemployed EmploymentStatus=Unemployed 440 ==> AgencyClassification=Unemployed 440 <conf(11)> lift:(3.32) lev:(0.21) [337] conv:(107.62)

```

Fig. 10. Best Rules found using Predictive Apriori Algorithm

V. CONCLUSION

Every year, the number of graduates produced by Higher Education Institutions (HEI) increases. The scenario is that the number matches job opportunities in the industry. The study provides valuable information about the graduate employment status, forecasting, visualization, and the exploration of classifiers algorithm to analyze the graduate employability

in government, non-government organizations, self-employed, and unemployed.

VI. RECOMMENDATIONS

The conduct of graduate tracer analysis on the different programs and relate the graduate employability to curriculum assessment and performance evaluation of graduates to identify measures and policies to improve student's performance.

TABLE I. FACTOR LOADING

Factor Number	Factor Name	% Variance
Factor 1	Course Structure and Diversity	25.194%
Factor 2	Affordability and Credibility	15.455%
Factor 3	Brand Value	12.060%
Factor 4	Competition	10.104%
Factor 5	Trend and Interests	6.884%

REFERENCES

1. H. P. Nudzor and F. Ansah, "Enhancing post-graduate programme effectiveness through tracer studies: the reflective accounts of a Ghanaian nation-wide graduate tracer study research team," *Qual. High. Educ.*, vol. 26, no. 2, pp. 192–208, 2020, doi: 10.1080/13538322.2020.1763034.
2. I. Djan and S. R. Adawiyyah, "A new decade for social changes," *Tech. Soc. Sci. J.*, vol. 17, pp. 235–243, 2021.
3. F. N. Romadlon and M. Arifin, "Improving Graduate Profiles Through Tracer Studies at University," *KnE Soc. Sci.*, vol. 2021, pp. 34–44, 2021, doi: 10.18502/kss.v5i7.9317.
4. S. Andari, A. C. Setiawan, and A. Rifqi, "Educational Management Graduates : A Tracer Study from Universitas Negeri Surabaya , Indonesia," vol. 2, no. 6, pp. 671–681, 2021.
5. B. H. Et.al, "Tracer Study Analysis for the Reconstruction of the Mining Vocational Curriculum in the Era of Industrial Revolution 4.0," *Turkish J. Comput. Math. Educ.*, vol. 12, no. 3, pp. 3013–3019, 2021, doi: 10.17762/turcomat.v12i3.1335.
6. M. E. Caingcoy, "Scoping Review on Employability Skills of Teacher Education Graduates in the Philippines: A Framework for Curriculum Enhancement," *Int. J. Educ. Lit. Stud.*, vol. 9, no. 4, p. 182, 2021, doi: 10.7575/aiac.ijels.v.9n.4p.182.
7. E. Cagasan, B. Belonias, and M. E. Cuadra, "Graduate Students' Perceived Contribution of Scholarship Grants to Academic Success," *Sci. Humanit. J.*, vol. 13, no. 1, pp. 99–113, 2019, doi: 10.47773/shj.1998.121.8.
8. A. P. Dela Rosa and G. Galang, "Bachelor of Science in Information Technology at Bulacan State University: A Graduate Tracer Study," *Int. J. English Lit. Soc. Sci.*, vol. 6, no. 3, pp. 265–272, 2021, doi: 10.22161/ijels.63.36.
9. R. A. Steenbruggen, M. J. M. Maas, T. J. Hoogeboom, P. L. P. Brand, and P. J. van der Wees, "The application of the tracer method with peer observation and formative feedback for professional development in clinical practice: a scoping review," *Perspect. Med. Educ.*, 2021, doi: 10.1007/s40037-021-00693-6.
10. M. Tapfuma, O. Chikuta, F. N. Ncube, R. Baipai, P. Mazhande, and V. Basera, "Graduates' Perception of Tourism and Hospitality Degree Program Relevance To Career Attainment: a Case of Graduates From Three State Universities in Zimbabwe," *J. Tour. Culin. Entrep.*, vol. 1, no. 2, pp. 190–207, 2021, doi: 10.37715/jtce.v1i2.2185.
11. D. C. Bueno, T. R. Dumlaio, M. H. Lopez, and J. G. Manago, "Tracing CCI education graduates: How well are we in developing professional teachers? Tracing CCI education graduates: How well are we in developing professional teachers? VP for Lifelong Learning and Students Welfare," *CC J. A Multidiscip. Res. Rev.*, vol. 15, no. March, 2020, doi: 10.13140/RG.2.2.18081.35686.
12. E. C. Deblois, "The Employment Profile of Graduates in a State University in Bicol

- Region, Philippines,” *J. Educ. Manag. Dev. Stud.*, vol. 1, no. 1, pp. 33–41, 2021, doi: 10.52631/jemds.v1i1.10.
13. S. Khadragy and S. Abdallah, “Adaptive Network Based Fuzzy Inference System and the Future of Employability,” *Netw. Complex Syst.*, no. April, pp. 24–32, 2021, doi: 10.7176/ncs/12-04.
 14. K. C. Piad, M. Dumlao, M. A. Ballera, and S. C. Ambat, “Predicting IT employability using data mining techniques,” 2016 3rd Int. Conf. Digit. Inf. Process. Data Mining, *Wirel. Commun. DIPDMWC 2016*, no. July, pp. 26–30, 2016, doi: 10.1109/DIPDMWC.2016.7529358.
 15. M. A. Job, “Data Mining Techniques Applying on Educational Dataset to Evaluate Learner Performance Using Cluster Analysis,” *Eur. J. Eng. Res. Sci.*, vol. 3, no. 11, pp. 25–31, 2018, doi: 10.24018/ejers.2018.3.11.966.
 16. Z. Othman, S. W. Shan, I. Yusoff, and C. P. Kee, “Classification techniques for predicting graduate employability,” *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 8, no. 4–2, pp. 1712–1720, 2018, doi: 10.18517/ijaseit.8.4-2.6832.
 17. S. Hizam, “A Research Study by Delphi Technique in School Counseling,” *Test*, vol. 82, no. 5607, pp. 5607–5615, 2020, doi: 10.5281/zenodo.4306058.
 18. S. F. S. Syeda Farha Shazmeen, “Performance Evaluation of Different Data Mining Classification Algorithm and Predictive Analysis,” *IOSR J. Comput. Eng.*, vol. 10, no. 6, pp. 1–6, 2013, doi: 10.9790/0661-1060106.
 19. O. M. Karatepe, O. Uludag, I. Menevis, L. Hadzimehmedagic, and L. Baddar, “The effects of selected individual characteristics on frontline employee performance and job satisfaction,” *Tour. Manag.*, vol. 27, no. 4, pp. 547–560, 2006, doi: 10.1016/j.tourman.2005.02.009.
 20. B. Jantawan and C. Tsai, “A Classification Model on Graduate Employability Using Bayesian Approaches: A Comparison,” *Int. J. Innov. Res. Comput. Commun. Eng. (An ISO Certif. Organ.)*, vol. 3297, no. 6, pp. 4584–4588, 2007, [Online]. Available: www.ijirccce.com.
 21. S. Thatavarti and K. Thammi Reddy, “Spice: A perspective approach for gap analysis to improve student performance index,” *Int. J. Appl. Eng. Res.*, vol. 12, no. 19, pp. 8651–8659, 2017.
 22. R. Wirth, “CRISP-DM: Towards a Standard Process Model for Data Mining,” *Proc. Fourth Int. Conf. Pract. Appl. Knowl. Discov. Data Min.*, no. 24959, pp. 29–39, 2000.
 23. K. J. Cios, R. W. Swiniarski, W. Pedrycz, and L. A. Kurgan, “The Knowledge Discovery Process,” *Data Min.*, pp. 9–24, 2007, doi: 10.1007/978-0-387-36795-8_2.
 24. P. Kurgan, L.A., Musilek, “A survey of Knowledge Discovery and Data Mining Process Models,” *Knowl. Eng. Rev.*, vol. 21, no. 1, pp. 1–24, 1996.
 25. T. Scheffer, “Finding association rules that trade support optimally against confidence,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 2168, pp. 424–435, 2001, doi: 10.1007/3-540-44794-6_35.