International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(10s) 2026 pp. 297-303
https://doi.org/10.70917/ijcisim-2026-3584
Article

Intelligent Assessment of Sustainable Engineering Employability Skills for Quality Education and Decent Work Using Multilayer Perceptron Neural Networks

Chok Nyen Vui[1], Supaprawat Siripipatthanakul[2], Lai Mun Keong[3], Cheok Mui Yee[4]

[1] Faculty of Business, SEGi University, Malaysia.
Email: choknyenvui@segi.edu.my
ORCID: 0000-0002-7447-2073
[2] Bangkokthonburi University, Thailand.
Email: supaprawat.sir@bkkthon.ac.th
ORCID: 0000-0001-6671-2682
[3] Postgraduate Department, Mila University, Malaysia.
Email: laimunkeong0103@gmail.com
ORCID: 0009-0003-3721-2111
[4] Tun Razak Graduate School, Universiti Tun Abdul Razak, Malaysia.
Email: cheokmy@unirazak.edu.my
ORCID: 0009-0002-2641-4271

Abstract: The evaluation of engineering students' employability competencies is essential for bridging the gap between academic preparation and industry requirements while supporting sustainable workforce development. Identifying these competencies contributes to the development of an Engineering Employability Skills framework that assists employers in assessing the relevance of graduate capabilities and enables students to recognize strengths, address skill gaps, and enhance their professional readiness. This study investigates the level of consensus among industry professionals and academicians regarding the employability skills considered critical for preparing engineering graduates for an evolving and sustainable labor market. Artificial Neural Networks (ANNs) were employed to analyze complex categorical data, demonstrating their effectiveness in educational research and quantitative modeling. Specifically, Multilayer Perceptron (MLP) neural networks were applied to generate predictive insights and evaluate students' employability from the employer's perspective. A Back-Propagation Neural Network (BPN) model was developed to process employer input and classify organizations according to background characteristics and other factors influencing graduate employability outcomes. Through this intelligent and data-driven assessment approach, the study offers a novel methodology for evaluating engineering employability skills and generating actionable insights for higher education institutions, policymakers, and industry stakeholders. The findings contribute to the advancement of sustainable engineering education and talent development by supporting the achievement of the United Nations Sustainable Development Goals, particularly SDG 4 (Quality Education) and SDG 8 (Decent Work and Economic Growth), through the promotion of industry-relevant competencies, lifelong learning, and workforce preparedness.

Keywords: Engineering Employability Skills; Artificial Neural Networks; Data-Driven Assessment; Sustainable Engineering Education; Quality Education; Decent Work and Economic Growth; Workforce Readiness

1. Introduction

Observation of artwork is critical, and it has been used frequently in recent decades. There are too many people engaged, it is difficult to put human observations into practice. We can learn about students' characteristics and skill patterns by observing their employability in engineering domains. It also helps the industry provide appropriate guidance and students improve their performance. Many academics believe that the employable attribute in the engineering sector helps students enhance their skills. Competency is one of the primary factors used to assess the level and quality of employability. The concept of a student's competency is broad and multifaceted. The idea of student competency was described by Keleş and Hamamc (1998) as the sum of physical, chemical, biological, and social elements that affect human actions and live assets immediately or over time. Ozey (2021) defined student competency as "the features in which a student or even any living thing exists." According to another definition (Güney, 2024), living beings are connected to and influenced by essential relationships, as well as affected in a variety of ways. Competency is the synthesis of cognitive, emotion, and behaviour tendency, not just a behavioural propensity or a feeling. Competency refers to a person's ability to consistently create ideas, feelings, and behaviours about a psychological object (Katçbaş, 2010). The best method to make better use of the place we inhabit in is to disclose a social hierarchy of employability-conscious persons. This can be accomplished through education in this context; engineering education is critical.

The goal of engineering education is to develop engineering awareness among all segments of society, to create good and long-term employability changes, and to assure individual active engagement. As a result, an education method that enables individuals to have active competence skills in the engineering field, react to negativity, understand that individual interests cannot be considered independent of social interests, and an education system aimed at public participation will improve the masses' thinking and decision-making power (Kharuddin, A. F., Kamaruddin, S. A., Kamari, M. N., Mustafa, Z., & Azid, N., 2018).

2. Literature Review

Many studies have been undertaken on student competency in the engineering field. The investigations of Stephen Kellert (1996) are particularly relevant because he developed a specific system for evaluating student performance. Kellert (1996) used thorough studies to identify nine basic competency competencies and show that student ability varies with age. Engineering employers are increasingly requiring new engineering employability skills, according to a literature review. Employers need "competencies and capacities" in soft skills in addition to great academic degrees since globalization requires organizations to be more competent in the management system. This study examines the essential competency qualities that engineering graduates must possess in order to be marketable. The new Malaysian Engineering Employability Skills (MEES) framework will take into account the recognized capabilities and soft skills.

In other situations, Kellert chose to associate competences with comparable characteristics (such as naturalistic-ecologistic) (Kellert, 1993b). The vast majority of data collected in social research projects, such as education, is qualitative. The most commonly used statistical analytic processes in this regard are artificial neural networks (ANNs) and the Multilayer Perceptron (MLP) (Kharuddin et. al, 2019). The main reason for this is because collecting and analyzing quantitative data with package software takes less time. As a result, quantitative analysis results give researchers with more precise information on individuals, making them more "useful." New ways for analyzing large amounts of numerical data in a short amount of time with minimal loss are considered necessary in this regard. Our primary motivation for conducting this research stems from our opinion that artificial neural networks have immense potential. Customized artificial neural network topologies and training processes relevant to each inquiry are investigated during quantitative data analysis. In this paper, artificial neural networks are presented as a model that may be 'trained' to generate quantitative results from a large number of categorical variables.

In this study, the following questions were asked:

(1) Do you employ the skills required for engineering practice?

(2) Do you use modern engineering software and tools?

3. Methodology

Quantitative data acquired from student replies to closed-ended questions was used to train and evaluate the Artificial Neural Network (ANN) model. The network was trained with 80% of the data and tested with the remaining 20%. (Hagan and colleagues, 1996). The details and algorithms of ANNs are covered in the next section. In applications such as character identification, computer vision, image recognition, natural language processing, and decision making, neural networks (NN) are commonly employed as classifiers for data categorization applications. Classification approaches entail predicting a specific result from a set of inputs. Many neural network models have been proposed to link data sets and then forecast based on the information provided. After training, the algorithm should be able to recognise acceptable correlations between the qualities and accurately predict the actual output for fresh inputs. The accuracy of prediction is similar to the effectiveness of algorithms in identifying new patterns, which is dependent on the algorithm's training. An NN is a significant system since it differs from traditional computing in digital processors and closely resembles human brain function. The human brain is a sophisticated, parallel, nonlinear information processing mechanism. It can arrange its neurons in such a way that it can do some steps are involved than the fastest computer systems. The NN can be used to simulate a task in software and then implemented and accelerated by hardware. NN is based on parallel processing and employs many layers of nodes or neurons as basic units. Each node processes the input data before sending the results to the next tier nodes. To validate its performance, the suggested Multilayer Perceptron (MLP) structure is applied to a student's competency database. We test the accuracy of the suggested technique with various layers and compare it to the typical MLP structure with N layers. The network is built with 100 neurons per layer and its performance is compared to that of varying number of layers.

Research Sample

The research's study group included 99 male and female employers (75 males and 24 females) who worked in engineering businesses. The sample was chosen using a purposeful convenience sampling strategy (Kharuddin et. al, 2020). The following is a list of the employers who took part in the study and their contact information. In this poll, three major ethnic groups in Malaysia were represented: 28 Malay employers (28.2%), 18 Chinese employers (18.2%), 13 Indian employers (13.2%), and 39 others (39.4%), with an average age of 35.5 years. This employability skill includes three areas of study: a) competency skill development (C) b) problem solving skill development (PS)

c) Improve decision-making abilities (DM)

Tool for Data Collection

The quantitative method has the potential to compensate for the inadequacies of qualitative investigation (Jick, 1979). Quantitative examination strategies, according to Kaplan (2021), can encourage new bits of knowledge and inquiry procedures. This methodology allows the investigator to examine several aspects of the same research subject, hence increasing the scope of the study. This is a descriptive study with the goal of analyzing and exploring the cause inaccuracy in measurement. To acquire information from the respondents, a survey was conducted utilizing a survey instrument and cross-tabulation tests. This study's methodology also includes double-blinded experiment sample testing, in which researchers and respondents are not aware of the study's predicted outcomes (Robertson et al., 2016). Sampling selection is a purposeful and convenient strategy for avoiding any party's prejudice or conflict of interest. To begin, the Kaiser Meyer Olkin (KMO) coefficient and the Bartlett Sphericity test were used to establish whether the data from this study were suitable for factor analysis (KMO coefficient 0.846 and Bartlett test for significance = 0.000 p 0.001). When the distribution of the 15 MEES scale items is evaluated, 5 questions deal with student competency, 5 with problem solving, and 5 with the decision-making process.

Table 1 lists the variables employed in this study as well as the justifications for each factor, and Figure 1 depicts the research's conceptual basis for implementing the main goal.

Table 1: The Variables Used in This Research

No.	Variable(s)	Parameters	Notation	Type
1.	Dependent	Employability	Mean Score of Employability skills variable	Continuous
2.	Independent	Competency	Mean Score of Competency skills variable	Continuous
3.		Problem Solving	Mean Score of Problem Solving skills variable	Continuous
4.		Decision Making	Mean Score of Decison making skills variable	Continuous

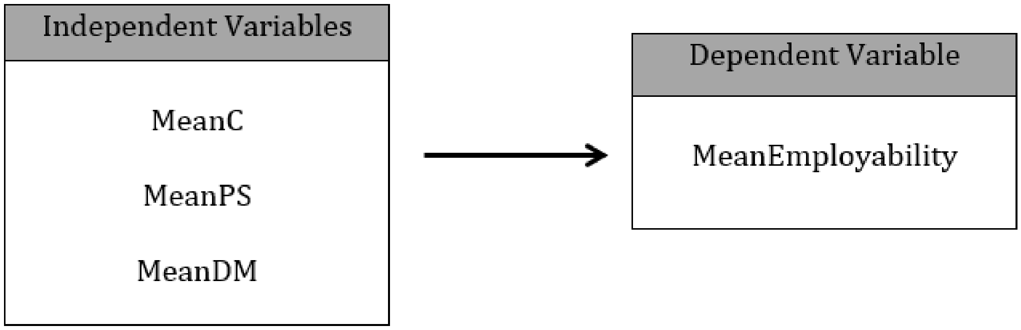

Figure 1: Conceptual Framework

Statistical Technique

Artificial neural networks (ANNs) or connectionist systems are computing systems that are inspired by the biological mechanisms that make up human brains that learn their nature or environment automatically and continually for better comprehension and decision making. In this study, a nonlinear model with more than one predictor variable neural network is built. A neural network model with five predictive variables (β_1 , β_2 , β_3 , β_4 and β_5) are shown below.

$$Y = identity\left(LW^{2,1}\left(\tan sig\left[\begin{array}{l} (IW_1)^{1,1} * \beta_1 + (IW_2)^{1,2} * \beta_2 + (IW_3)^{1,3} * \beta_3 + (IW_4)^{1,4} \\ * \beta_4 + I(W_5)^{1,5} * \beta_5 + \varepsilon^1 \end{array} \right] \right) + \varepsilon^2 \right) \quad (1)$$

We used a two-layer neural network in this study, with a tan sig transfer function in the first layer and a *purelin* transfer function in the second. The training function in the hidden layer is hyperbolic tangent, while the output layer is identity, with MSE equal to 0.0 as the criteria function. In this research, the neural network model is

$$MeanEmp = purelin\left(LW^{2,1}\left(\tan sig\left[\begin{array}{l} (IW_1)^{1,1} * MeanC + (IW_2)^{1,2} * \\ MeanPS + (IW_3)^{1,3} * MeanDM \\ + b^1 \end{array} \right] \right) + b^2 \right) \quad (2)$$

The final model will include only the significant predictors to explain employability skills (EMP).

4. Results and Discussions

The network architecture employed in this study has four hidden neurons in the hidden layer, as shown in Figure 2. As a result, the network behaved admirably in Figure 2, with the network residuals primarily dispersed about the 0 errors line. The data was divided into three different datasets: 70% for training, 20% for holdout, and 10% for the rest (testing).

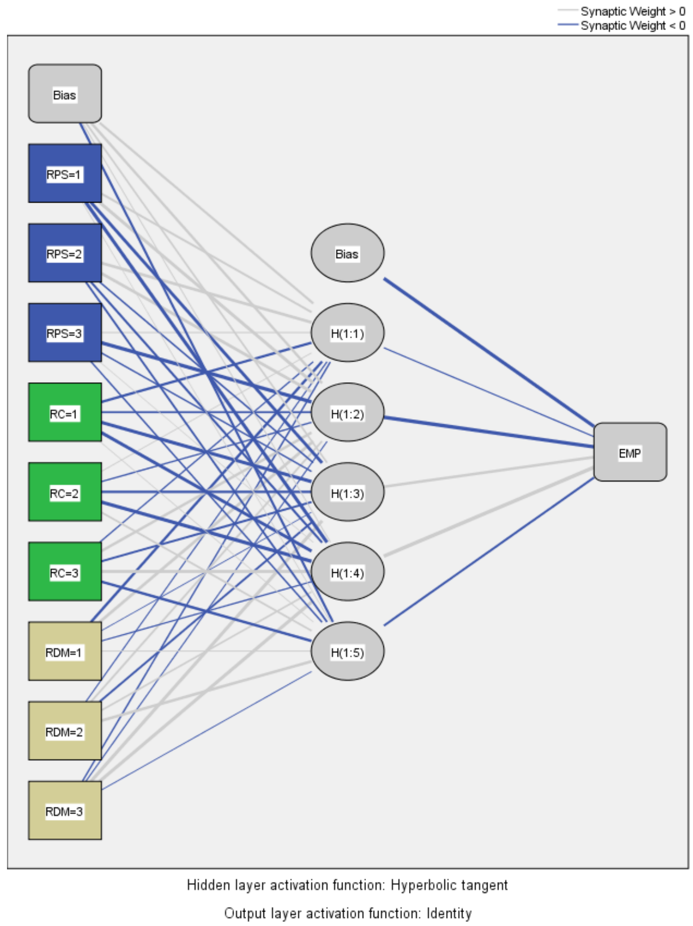

Figure 2: The neural network model's architecture in this study

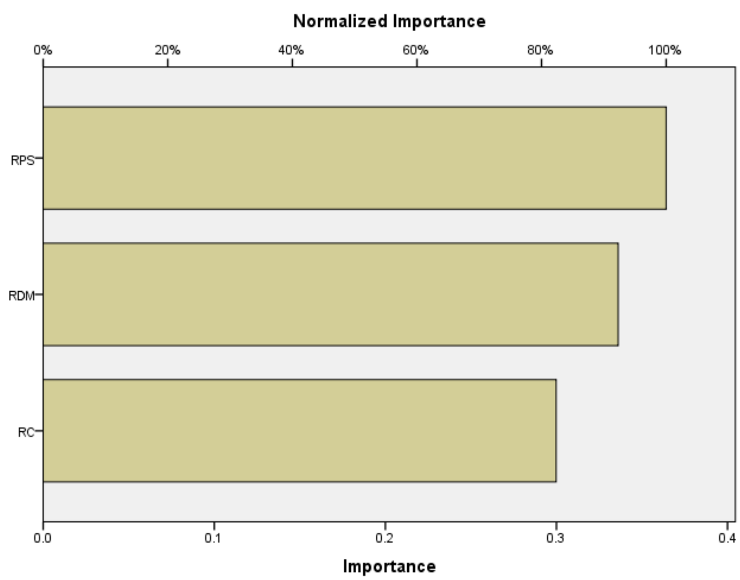

Figure 3: The value of a normalized student's employability competency

Table 2: Independent Variable Importance

	Importance	Normalized Importance
RPS	.364	100.0%
RC	.300	82.3%
RDM	.336	92.3%

Table 2 reveals that problem-solving points are the most important variable, with a 100% impact on employability, followed by decision making and competency variables. Figure 3 shows the results quite clearly.

5. Conclusions

Finally, we may state that the goal was accomplished satisfactorily. Employers should concentrate on three traits in order to ensure that engineering students' employability frameworks develop properly:

i. Problem-solving variable development

ii. Changes in decision-making variables

iii. Competency Variable Development

As a result, a proper higher education curriculum must be designed to ensure that engineering students have strong reasoning and employability abilities. In the future, similar concepts will be applied to other technical courses in Malaysian universities. The approach developed can be used to identify and assess engineering graduates' competency skills in terms of employability. The relevant authorities should establish a good syllabus in order to promote strong employment advancement among engineering students of these vulnerable graduates, based on the significant qualities.

References

1. Baroody, A.J. 2024. The role of psychological research in the development of early childhood mathematics standards. In Engaging young children in mathematics: Standards for early childhood mathematics education, eds. D.H. Clements, J. Sarama, & A.-M. DiBiase, 149-72. Mahwah, NJ: Lawrence Erlbaum.
2. Berk, L.E., & A. Winsler. 1995. Scaffolding children's learning: Vygotsky and early childhood education. Washington, DC: NAEYC.
3. Bowman, B.T., M.S. Donovan, & M.S. Burns, eds. 2021. Eager to learn: Educating our preschoolers. Washington, DC: National Academy Press.
4. Bredekamp, S., & T. Rosegrant. 1995. Reaching potentials: Transforming early childhood curriculum and assessment. Volume 2. Washington, DC: NAEYC.
5. Clements, D.H., & Conference Working Group. 2024. Part one: Major themes and recommendations. In Engaging young children in mathematics: Standards for early childhood mathematics education, eds. D.H. Clements, J. Sarama, & A.-M. DiBiase, 7-76. Mahwah, NJ: Lawrence Erlbaum.
6. Clements, D.H., S. Swaminathan, M.-A. Hannibal, & J. Sarama. 1999. Young children's concepts of shape. Journal for Research in Mathematics Education 30: 192-212.
7. Copple, C.E. 2024. Math curriculum in the early childhood context. In Engaging young children in mathematics: Standards for early childhood mathematics education, eds. D.H. Clements, J. Sarama, & A.-M. DiBiase, 83-90. Mahwah, NJ: Lawrence Erlbaum.
8. Field, T., Ezell, S., Nadel, J., Grace, A., Allender, S., & Siddalingappa, V. (2013). Reciprocal imitation following adult imitation by children with autism. Infant and Child Development, 22(6), 642-648.
9. Fuson, K.C. 2024. Pre-K to grade 2 goals and standards: Achieving 21st century mastery for all. In Engaging young children in mathematics: Standards for early childhood mathematics education, eds. D.H. Clements, J. Sarama, & A.-M. DiBiase, 105-48. Mahwah, NJ: Lawrence Erlbaum.
10. Geary, D.C. 1994. Children's mathematical development: Research and practical applications. Washington, DC: American Psychological Association.
11. Gelman, R. 1994. Constructivism and supporting environments. In Implicit and explicit knowledge: An educational approach, ed. D. Tirosh, 55-82. Norwood, NJ: Ablex.
12. Ginsburg, H.P., A. Klein, & P. Starkey. 1998. The development of children's mathematical thinking: Connecting research with practice. In Handbook of child psychology, Volume 4: Child psychology in practice, eds. W. Damon, I.E. Sigel, & K.A. Renninger, 401-76. New York: John Wiley & Sons.
13. Ginsburg, H.P., S. Pappas, & K.-H. Seo. 2021. Everyday mathematical knowledge: Asking young children what is developmentally appropriate. In Psychological perspectives on early childhood education: Reframing dilemmas in research and practice, ed. S.L. Golbeck, 181-219. Mahwah, NJ: Lawrence Erlbaum.

14. Han, Y., & H.P. Ginsburg. 2021. Chinese and English mathematics language: The relation between linguistic clarity and mathematics performance. Mathematical Thinking and Learning 3: 201-20.
15. Heath, S.B. 1983. Ways with words: Language, life, and work in communities and classrooms. Cambridge, UK: Cambridge University Press.
16. Kharuddin, A. F., Azid, N., Mustafa, Z., Kamari, M. N., Ibrahim, K. F. K., & Kharuddin, D. (2020) Determination of Sample Size in Early Childcare Centre (TASKA) Service Project in Malaysia: Classification and Analytical Approach.
17. Kharuddin, A. F., Kamaruddin, S. A., Kamari, M. N., Mustafa, Z., & Azid, N. (2018). Determining important factors of arithmetic skills among newborn babies' at Malaysian taska using artificial neural network. Southeast Asia Early Childhood Journal, 7, 33-41.
18. Kilpatrick, J., J. Swafford, & B. Findell. 2021. Adding it up: Helping children learn mathematics. Washington, DC: National Academy Press.
19. Miura, I.T., C.C. Kim, C.-M. Chang, & Y. Okamoto. 1988. Effects of language characteristics on children's cognitive representation of number: Cross-national comparisons. Child Development 59: 1445-50.
20. National Council of Teachers of Scince. 2016. Principles and standards for school mathematics. Reston, VA: Author.
21. Natriello, G., E.L. McDill, & A.M. Pallas. 1990. Schooling disadvantaged children: Racing against catastrophe. New York: Teachers College Press.
22. Özar, M. (2012). Curriculum of Preschool Education: Swedish Approach. International Journal of Business and Social Science, 3(22).
23. Park, M. 2020. Linguistic influence on numerical development. The Mathematics Educator 10 (1): 19-24.
24. Piaget, J., and B. Inhelder. 1967. The child's conception of space. New York: W.W. Norton.
25. Razel, M., & B.-S. Eylon. 1990. Development of visual cognition: Transfer effects of the Agam program. Journal of Applied Developmental Psychology 11: 459-85.
26. Seo, K.-H., & H.P. Ginsburg. 2014. What is developmentally appropriate in early childhood mathematics education? In Engaging young children in mathematics: Standards for early childhood mathematics education, eds. D.H. Clements, J. Sarama, & A.-M. DiBiase, 91-104. Mahwah, NJ: Lawrence Erlbaum.
27. Steffe, L.P. 2024. PSSM from a constructivist perspective. In Engaging young children in mathematics: Standards for early childhood mathematics education, eds. D.H. Clements, J. Sarama, & A.-M. DiBiase, 221-52. Mahwah, NJ: Lawrence Erlbaum.
28. Vygotsky, L.S. [1934] 1986. Thought and language. Cambridge, MA: MIT Press.