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Neural Network Techniques in Analysing the TVET Instructor Competency Assessment

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This study examines the influence of year of working experience on the competency assessment of technical vocational education and training (TVET) instructors using neural networks (NN) and the Curriculum Development Based on Ability Structure (CUDBAS) method. However, despite the widespread use of competency assessments, there remains a lack of a methods that includes year of working experience on instructor competency, which is crucial for training needs analysis (TNA). Experienced TVET instructors are pivotal in training delivery and development, making competency and ability assessments essential. To address this gap, this study applies the combination of CUDBAS Ability Map and NN method to evaluate TVET instructors' competency. Data from three certification courses were analysed using feedforward NN (FFNN) and cascade forward NN (CFNN) models. Neurons in the models ranged from 10 to 50, with performance assessed via regression, mean square error (MSE), mean, and standard deviation. Results show that FFNN and CFNN perform comparably for Courses 1 and 2, while FFNN slightly outperforms CFNN in Course 3, with a 0.2% higher regression value and lower MSE with 11.4% in Course 1, 1.01% in Course 2, and 2.25% in Course 3. Both FFNN and CFNN successfully identified the influence of year of working experience on TVET instructors' Ability Map assessments, highlighting their potential in enhancing competency evaluations.

Keywords: TVET; neural network; CUDBAS; training need analysis; Ability Map

I. INTRODUCTION

TVET is an acronym that stands for technical and vocational education and training. TVET is an education and training procedure with an occupational focus that emphasised on industrial practises. In Malaysia, the TVET direction is to produce skilled workers in selected sectors via TVET institutions, starting from secondary school to higher education levels. The direction of TVET institutions was based on recognised employment standards, with a focus on practical aspects, psychomotor skills, and exposure to industry training (Yasak & Alias, 2015). There is a need for evaluating job ability competency and function of TVET instructors (Wilk & Sackett, 1996).

Empowering TVET instructor skills and knowledge can increase the quality of graduates from TVET institutions (Syamil & Bassah, 2022). Continuous training needs analysis (TNA) was found to be significant in strengthening TVET instructor competency (Kim *et al.*, 2019). Competency mapping, interviews, surveys form, focus groups, and

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vocational ability structures are the TNA methods to evaluate TVET instructor ability competency (Kim *et al.*, 2019; Zinn *et al.*, 2019; Abba & Rashid, 2020; Wan Ngah *et al.*, 2021). Competency mapping is one of the TNA methods applied to assess competency. Competency mapping involves identifying the essential skills and knowledge that trainees need to acquire as a result of participating in the training process (Harraf *et al.*, 2019). The interview approach was conducted with an individual or focus group for three times, with video recording as the data collected (Abba & Rashid, 2020). In surveys form technique, the 5-point Likert scale was used to measure the "attitude" in scientific order known as accepted and validated (Joshi *et al.*, 2015). The focus group technique was based on the targeted sets of input and specialisation (Zinn *et al.*, 2019). The vocational ability structure technique applies four competency profiles known as (i) competency need study, (ii) identifying competency need, (iii) reducing competency gap, and (iv) TVET instructor recognition (Wan Ngah *et al.*, 2021).

Another method that was applied to assess vocational ability is the curriculum development based on ability structure (CUDBAS) method. The CUDBAS method is a TNA method invented by Prof. Dr. Kazuo Mori from Japan in 1990 (Affero Ismail *et al.*, 2019; Mori, 2019). The innovation of the CUDBAS method helps in improving the TNA. The CUDBAS method was used to develop the Ability Map. The Ability Map is used to carry out the self-assessment competency of the TVET instructor based on the job profile and skill set. The Ability Map examined the TVET instructor competency in terms of the attitude, skill, and knowledge that are also known as A, S, and K, respectively. The outcome of Ability Map assessment is the TVET instructor's ability competency based on job profile and skill set scores. The scope of the Ability Map developed using the CUDBAS method can extend beyond curriculum development to include employment, entrance exams, training, and evaluation (Wan Ngah *et al.*, 2021). The CUBDAS Ability Map assessment scores were interpreted based on the mean and standard deviation. The mean for the Ability Map of a TVET instructor is between 2.73 and 4.14, whereby for the standard deviation, the value is between 0.607 and 1.145 (Kim *et al.*, 2019; Dadi, 2017). The working experience shows a significant impact on the TVET instructor's ability and competency, where the mean value is between 4.23 and 4.71 whereby the standard deviation is between 0.41 and 0.64 (Abdullah *et al.*, 2022).

The influence of employee experience on TNA manifests across several critical dimensions. First, skill discrepancies vary significantly with experience levels in which entry-level employees typically require fundamental training, whereas seasoned employees benefit from advanced or leadership-oriented programs designed to address their specialised needs (Kura & Supreet Kaur, 2021). Second, the efficacy of training programs is closely linked to employee experience, with experienced personnel deriving greater benefits from specialised, role-specific training, while less experienced employees achieve optimal outcomes through foundational skill-building initiatives (Robert & Mori, 2024). Third, TNA serves as a pivotal mechanism for aligning training interventions with organisational objectives, ensuring that novice employees receive role-specific preparation while experienced staff are equipped for strategic and managerial challenges (Dierdorff & Surface, 2008). Finally, tailored training programs that align with the professional aspirations of experienced employees enhance engagement and foster retention, contributing to sustained workforce motivation and organisational stability.

The neural network (NN) is a computational technique that was widely used to address a wide range of challenging real-world issues. The NN learning strategies may consist of back-propagation, Kohonen, and counter-propagation (Zupan, 1994). The backpropagation of the network error and adjusting the interconnecting weights for each layer is an essential part of the network learning process, performed by the learning algorithm. The choice of the number of hidden neurons is left to the user (Rafiq *et al.*, 2001). In the Kohonen-NN, which is suitable for unsupervised systems, the network automatically adapts itself to create a topological mapping of input that is associated with topologically close neurons in the network (Zupan, 1994). The counter-propagation networks were applied in various domains, such as pattern recognition, data clustering, and prediction tasks (Zupan, 1994).

This study examines the impact of TVET instructors' year of working experience on their ability assessments using an innovative approach of CUDBAS Ability Map, that later addresses as Ability Map, combined with feedforward neural network (FFNN) and cascade forward neural network

(CFNN) technique. The CUDBAS method has proven effective in competency mapping, but its application has not been fully explored in relation to year of working experience (Mori, 2019; Wan Ngah *et al.*, 2021). In this study, a combination of the Ability Map from CUDBAS with FFNN and CFNN techniques is applied to evaluate the influence of year of working experience on TVET instructor competency assessments. By comparing the Ability Map assessment scores without considering year of working experience with FFNN and CFNN that include the year of working experiences, the study aims to provide insights into how year of working experience affects competency evaluation outcomes and to enhance the accuracy of TNA for TVET instructors.

II. MATERIALS AND METHOD

A. The Characteristic of Respondent

In current approached, TVET instructor profile on year of working experience was not evaluated. The TVET instructors scores on Ability Map assessment sheet without year of working experience was obtained from Institute Latihan Perindustrian (ILP) Jitra, Kedah, Malaysia. ILP is a technical industrial training institution under the Malaysia Manpower Department, Ministry of Human Resources. Three certification courses from ILP Jitra known as Electric Technology, Automotive Technology, and Heavy Commercial Vehicle Technology, also known as Course 1, 2, and 3 respectively, were chosen. The Ability Map assessment contains the information for duty, ability, score and standard deviation together with TVET instructor details. The TVET instructor profiles contain of name, department, course of training and year of working experience. In total, Courses 1, 2, and 3 have 69, 114, and 126 number of abilities measured in Ability Map assessment.

Compared to industrial experience, the majority of instructors have substantially greater teaching experience as seen in Table 1. While industry experience peaks at 14 years, teaching experience can span up to 30 years. Among the respondents, teaching experience predominates, however some TVET instructors display a balanced mix of the two. This illustrates how the instructors prioritise their teaching responsibilities over industry.

To start the analysis, firstly, the TVET instructors' year of working experience was clustered into 4 categories known as categories 1, 2, 3, and 4 or CAT 1, 2, 3, and 4, respectively, as seen in Table 2. 12 TVET instructors were under CAT 4, whereby only 2 were under CAT 1. The TVET instructors that possess working experience between 11 and 15 years are 16 people, whereas 3 TVET instructors have working experience between 6 and 10 years. The age of the TVET instructors who participated in this study was between 26 and 56 years old, with working experience between 4 and 30 years. The TVET instructor's working experience in industry is up to 14 years. The working experience in the current teaching course for the TVET instructor's is between 10 months and 30 years.

Figure 1 displays 33 TVET instructors' year of working experience, broken down by industry and teaching experience. Category 1, comprising 2 respondents, has an average of 1.42 years in teaching and 2.08 years in industry, totalling 3.5 years. CAT 2, with 3 respondents, shows an average of 3.17 years in teaching and 3.83 years in industry, amounting to 7 years. CAT 3, consisting of 16 respondents, demonstrates a higher average teaching experience of 10.69 years and 2.31 years in industry, resulting in 13 total years. Lastly, CAT 4, with 12 respondents, exhibits the most extensive experience, averaging 19.42 years in teaching and 4.42 years in industry, totalling 23.83 years of working experience.

Table 1. Average teaching and industry experience of TVET instructors by category

Parameter	Range/Value
Age of TVET Instructors	26 to 56 years
Total Working Experience	4 to 30 years
Industry Working Experience	1 to 14 years
Teaching Working Experience	10 months to 30 years
Instructors with Industry Experience	22 instructors (1 to 15 years' experience)

Table 2. The TVET instructor's working experience for course 1, 2 and 3

Category	Year of working experience	No. of correspondent
CAT 1	0 – 5	2
CAT 2	6 – 10	3
CAT 3	11 – 15	16
CAT 4	>16	12

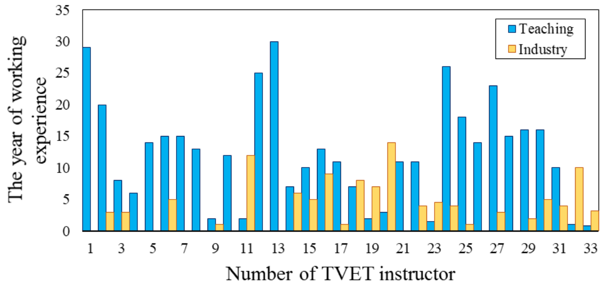


Figure 1. TVET instructors' year of working experience in current teaching course and industry

B. Assessment Method for TVET Instructor Competency

The manual of TVET Trainer Profile Development 2018 by the Centre for Instructor and Advanced Skill Training (CIAST), Shah Alam, Selangor, Malaysia, was used as a guideline for the Ability Map assessment preparation (Ismail, 2018). Currently, the TVET instructor performed self-assessment in block A1 using an Ability Map, which no parameter of year of working experience includes, as shown in Figure 2. For the proposed method of the Ability Map-NN technique, the year of working experience and the Ability Map assessment scores become inputs to the NN network. The results from the Ability Map assessment in block A1 were fed as input via the proposed path to block B1 and analysed by the NN technique.

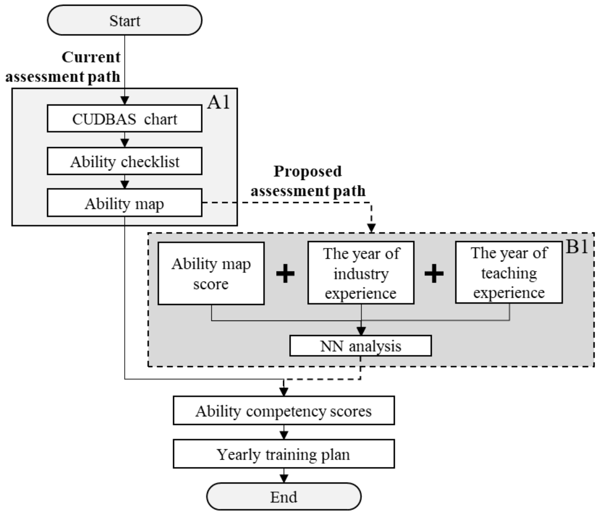


Figure 2. The TVET instructor ability competency assessment based on the Ability Map - NN technique flowchart

The CUDBAS method provides detailed direction related to the A, S, and K of the TVET instructor to do the task. The A is attitude, referring to behaviour in order to deliver the task. The ability to "do" something is the skill, or S, whereby K is the knowledge to understand on the theoretical part. Apart from that, the CUDBAS method also assists TVET institution in identifying and streamlining work processes, skill gap, increase training cost effectiveness, and upskilling planning for TVET instructor. The advantage of the CUDBAS method is that the development of Ability Map assessment is quick (Fata, 2016). On top of that, the application of the CUDBAS method in developing the Ability Map assessment is suitable to evaluate the level of skills for the TVET instructor. Subject matter experts (SME) and CUDBAS leaders are two categories of personnel involved in the CUDBAS method process. The SME is the personnel who is an expert in the specific TVET course, whereby the CUDBAS leader is the certified CUDBAS facilitator.

The process for the CUDBAS method chart development is included in block A1-Part I, as shown in Figure 3. The item (i) inside Part I is the procedure where the CUDBAS leader briefed the SME on the ethics and skill scope of the discussion. The SME will then prepare the ability and duty cards as shown in Figures 4(a) and (b). The contents of the ability card consist of the ability statement elements A, S, and K, as shown in Figure 4(a). The A, S, and K are defined based on the required tasks of a TVET instructor as stated in job profiles and course contents (Affero Ismail *et al.*, 2019).

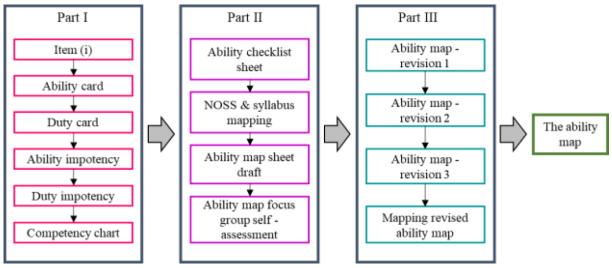


Figure 3. The development of Ability Map assessment flowchart

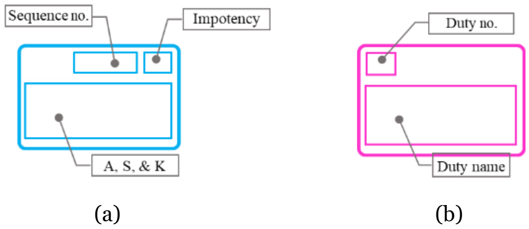


Figure 4. The CUDBAS method (a) ability and (b) duty card

In the development of ability cards, SME adheres to specific guidelines. SME should focus solely on educational abilities, avoiding personality or character traits. The process is solitary, with no discussion with others SME permitted. Each idea is expressed clearly and concisely within a maximum of three lines. Depending on the type of ability between A, S, or K, SME start their ability statement with appropriate keywords like "BE" for attitude, "CAN" for skills, and "KNOW" for knowledge. Ideas for ability statements can be derived from various factors, such as situational context, time of day, year, conditions, or individuals involved.

The duty cards, on the other hand, are named based on the number of ability statements that share similar concepts, ideas, or approaches. The duty name for the duty card reflects the overall ability statement with regard to the task, as seen in Figure 4(b). The duty name should be precise and straight-forward.

Once the SME has completed preparing the ability card, the importance level of each ability card needs to be represented using A, B, and C. The A represents the very important ability that is usually referred to as a skill that is extremely important, whereas the B and C are for moderate and not so important, for routine and less required skills. The sequence and duty number for the ability and duty card will be determined during the development of the CUDBAS method chart. In this study, the number of duties for Course 1, 2, and 3 is 15, 17, and 9, with 69, 114, and 126 number of abilities each.

The CUDBAS method chart is built by hardware or software after the duty and ability card is prepared, as seen in Figure 5 (Alfino Asmana, 2023). The CUDBAS leader guides the SME to arrange the duty and ability cards in the CUDBAS method chart. The arrangement of duty and ability cards is in horizontal form. The duty card needs to be placed on the left side of the CUDBAS method chart, while the ability card is on the right side. The A category ability card is in the early sequence, followed by the B and C. After all the ability and duty cards are arranged in the CUDBAS method chart, the sequence number and duty number for ability and duty cards are given. The title of the CUDBAS method chart is the course name.

Next, the CUDBAS leader will assist the SME in developing the first draft of the ability checklist. The information from the CUDBAS method chart is extracted to perform the ability checklist, as seen in Figure 6. An ability checklist is prepared using a table, either by software or hardware. Three columns are required for the ability statement number, impotency level, and ability statement. The ability checklist prepared by the SME is required to be mapped with Malaysia National Occupational Skill Standard (NOSS) or course syllabus to ensure the right competency, as shown in Part II in Figure 3. The NOSS is a document detailing the skills and proficiency expected from an employee working in Malaysia at a particular employment level to attain specific abilities (Amran *et al.*, 2020). NOSS contains a list of competency units and work activities for a specific working area, whereby the syllabus contains the course module, subject, or topic.

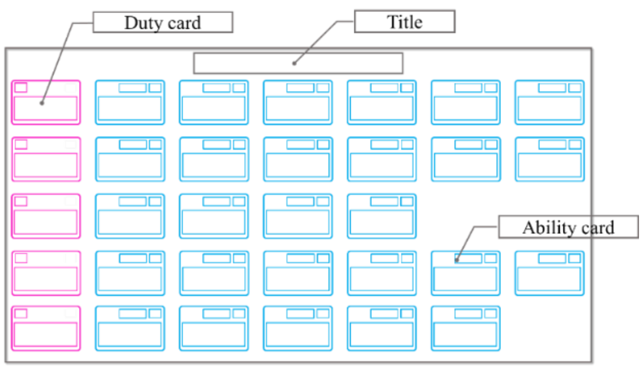


Figure 5. The CUDBAS method chart

No.	Impotency	Ability
Ability number	A, B or C	Ability statement based on A, S and K

Figure 6. Template for ability checklist

For mapping the ability checklist with NOSS, this step serves as the foundation to align the ability checklist with industry-relevant skills and knowledge. Next, the abilities required for each competency unit are mapped to their corresponding work activities. This mapping ensures a clear understanding of the skills needed to perform specific abilities effectively. Subsequently, it is essential to identify any work activities that are not directly related to existing abilities. These activities serve as indicators for potential gaps in the ability checklist. To bridge these gaps, new abilities from NOSS corresponding to these work activities should be added. Once the new abilities are incorporated, it is vital to review the entire ability checklist to guarantee its comprehensiveness and accuracy, ensuring that the training program covers all necessary skills and competencies essential for the targeted industry.

After the completion of the ability checklist mapped with the NOSS or syllabus reviewed by the CUDBAS leader and SME, the first draft of the Ability Map assessment is developed. The CUDBAS leader and SME performed self-assessment on the first draft of the Ability Map assessment to examine the consistency of the statement. The Ability Map assessment layout is shown in Figure 7.

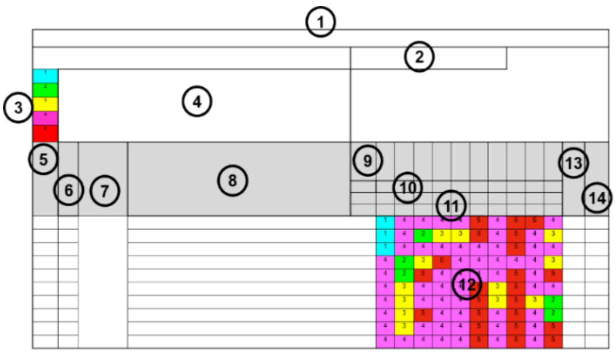


Figure 7. The Ability Map assessment sheet layout

There are 14 items in preparing the Ability Map. The course name and date of the Ability Map developed are at number 1 and 2. A colour code at number 3 was implemented to differentiate ability scores, where cyan is 1 and red is 5. The description of the ability score is placed at number 4 with the details. The ability score is inserted at number 12. The ability number was located in column number 5, followed by importance, duty, and ability checklists in columns number 6, 7, and 8, respectively. The TVET instructor name, year of working experience for industrial, and teaching are placed at number 9, 10, and 11. The results for the TVET instructor abilities are placed at column number 13 whereby standard deviation score is in column number 14. Three refinery process is performed by the SME and CUBDAS leader before the final Ability Map is produced, as seen in Part III in Figure 3. The CUDBAS method Ability Map assessment is then delivered to the TVET instructor to perform self-assessment (Wan Ngah *et al.*, 2021).

The Ability Map assessment for Courses 1, 2 and 3 consist of 33 TVET instructors with 309 list of ability statement involved. The Ability Map will result a score of technical trainer's ability competency based on mean and standard deviation. The scoring made by each TVET instructor is based on competency level ranging between 1 to 5 as shown in Table 3. The lowest ability is defined as dependent TVET instructor in performing task whereby the highest ability is defined as capable to become an TVET instructor to others. The mean and standard deviation scores in column no.13 and 14 are calculated based on all TVET instructors scores.

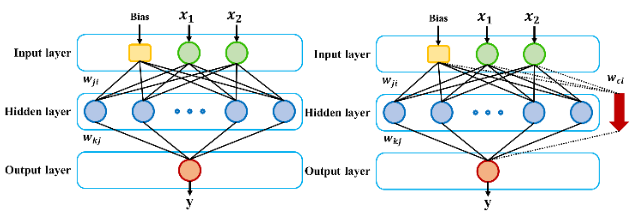
Table 3. The Ability Map scoring

Score	Description
1	Unable to do independent
2	Able to do but still need help
3	Able to do by their own
4	Fairly capable
5	Capable to do completely and can instruct other

The NN are modelled after the human brain. Human brain biological neuron consists of cell body, nucleus, synapses, axon, and dendrites. The dendrites receive an input and send this input in the form of electro-chemical signal into the cell body that contain nucleus. The nucleus processed this signal and deliver to another neuron via axon. In this study, feedforward neural network (FFNN) and cascade forward neural network (CFNN) is designed as shown in Figures 8(a) and 8(b), respectively. A single hidden layer was applied for FFNN and CFNN network architecture. CFNN offer a promising approach for conducting training needs analysis through CFNN dynamic learning capabilities and adaptability to small sample sizes (Mohamed *et al.*, 2021). By leveraging CFNN strengths in predictive modelling and incremental learning, organisations can better identify and address employee training needs effectively (Marquez *et al.*, 2015). On top of that, CFNN are well-suited for scenarios involving small sample sizes due to their dynamic architecture and ability to mitigate overfitting risks (Gaonkar *et al.*, 2016). This makes CFNN a valuable tool in fields where data scarcity is a significant concern (Gaonkar *et al.*, 2016).

The input vector is coming from the TVET instructor's year of working experiences; target vector is Ability Map assessment scores from A1 whereby the output is the new CUDBAS-NN scores. The input vector of x_1 and x_2 is represent the year of working experience on teaching and industry, respectively. In total, 3320 Ability Map assessment scores for all TVET instructor is supply to the input vectors. The hidden layer contains number of neurons. Number of neurons is varying from 10 to 50 with interval of 10 (Hashim *et al.*, 2023).

The cumulative data in from input layer is transfer to hidden layer. For FFNN, the weight, w_{ji} , is connected between input nodes and hidden layer nodes whereby for CFNN, there is a direct connection of weight, w_{ci}, from input nodes to output layer. Back-propagation technique is applied where the accumulated data in output layer is transfer back to hidden layer and the process repeated until the desired output gained and new Ability Map assessment scores, y, is produced. This process also known as epoch. The biases are implicitly handled by the function and training process. The biases are automatically initialised and included in the network's parameters.



(a) (b)

Figure 8. The architecture for (a) feedforward and (b) cascade forward neural network

Levenberg-Marquardt training type was chosen to train the network. Levenberg-Marquardt is a second order algorithm that has an advantage to handle small, median, and complex data size (Wilamowski & Yu, 2010), (Smith *et al.*, 2019). The output from a summation of the weighted neuron and inputs is calculated using the logsig and linear transfer functions, which are the two most used types of transfer functions (Hashim *et al.*, 2023; Kamaruddin & Shogar, 2011). The bias or neuron's threshold limit was used to activate the neuron (Basheer & Hajmeer, 2000). The value of bias was defined during the initialisation of then neural network.

An *a-b-c-d* configuration was used for the FFNN analysis as shown in Figure 9(a). The parameter, *a* is the number of inputs, *b* is the number of neurons in the hidden layer, *c* is the output process layer and *d* is the desired PD location. *a* and *c* are fixed to 2 which can be represented by x_1 and x_2 while *d* was set to 1. The parameter, *b* was set from 10 to 50. The FFNN activation is shown in Equation (1) and (2). The h_i is the i^{th} neuron in hidden layer, *logsig* is the activation function and w_{kj} represent the weight in the entry between hidden layers.

For CFNN analysis, there is a connection from *a* to *c* as seen in Figure 9(b). The *a* to *c* connection in CFNN can be further visualize in Equation (3). The w_{ci} is connected to output layer, *M* and *K* is then total number of layers, h_j is nodes in hidden layer, w_{kj} is weight firing from hidden layer, and w_{ci} is the weight firing from input layer. The advantage of cascade is the same input can behaves as different input (Venkadesan *et al.*, 2017; Dada *et al.*, 2021; Yan, Pin & He, 2021).

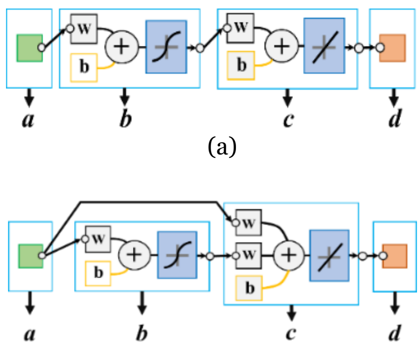


Figure 9. The layout for (a) FFNN and (b) CFNN analysis

$$h_i = logsig(\textstyle\sum_{j=1}^{M} x_i \bullet w_{ji}) \tag{1}$$

$$y = logsig(\textstyle\sum_{j=1}^{M} h_{j-1} \bullet w_{kj}) \tag{2}$$

$$y = logsig[(\textstyle\sum_{j=1}^{M} h_j \bullet w_{kj}) + (\sum_{j=1}^{K} w_{ci} \bullet x_i)] \tag{3}$$

III. RESULT AND DISCUSSION

A. Ability Map Assessment

Overall, there are 309 ability list in Ability Map assessment. The Ability Map assessment scores for Course 1, the CAT 1 to 4 scores primarily ranging between 4 and 5, indicating that Course 1 TVET instructors are highly experienced, as illustrated in Figure 10(a). However, a few CAT 3 scores are lower due to the duty that are related with safety, that are suggesting a need for further training on specific ability lists. For Course 2, the CAT 3 scores are concentrated around 1, because there are TVET instructors which are new to teaching experiences, as shown in Figure 10(b). The CAT 4 scores for Course 2 instructors' range between 2 and 5, while the CAT 1 scores fall between 2 and 3, attributed from junior instructor status. In Course 3, the majority of TVET instructors Ability Map assessment scores range between 2 and 5, as depicted in Figure 10(c).

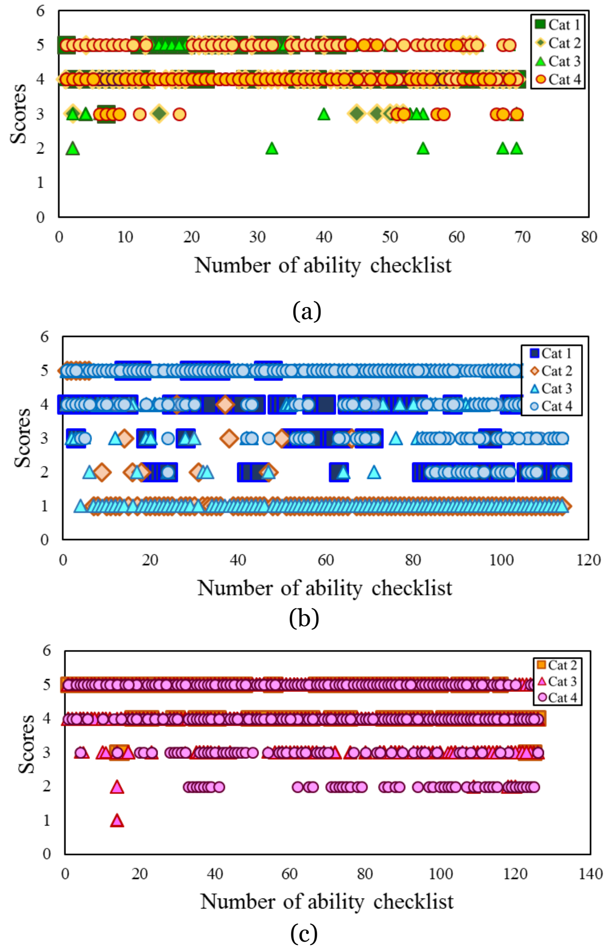


Figure 10. TVET instructors Ability Map assessment without year of working experience score for Course (a) 1, (b) 2 and (c) 3

The lowest Course 1 mean score for the Ability Map assessment without year of working experience is found for working experience between 11 and 15 years with 3.91 whereby the highest is for TVET instructors that have more than 16 years of working experience with mean value of 4.65, respectively, as seen in Figure 11(a). As for Course 2, the mean score for the Ability Map assessment is between 1.22 and 5 as shown in Figure 11(b). The Course 3 for the working experience more than 16 years has the highest mean score for the Ability Map assessment without working experience with 4.46 as seen in Figure 11(c).

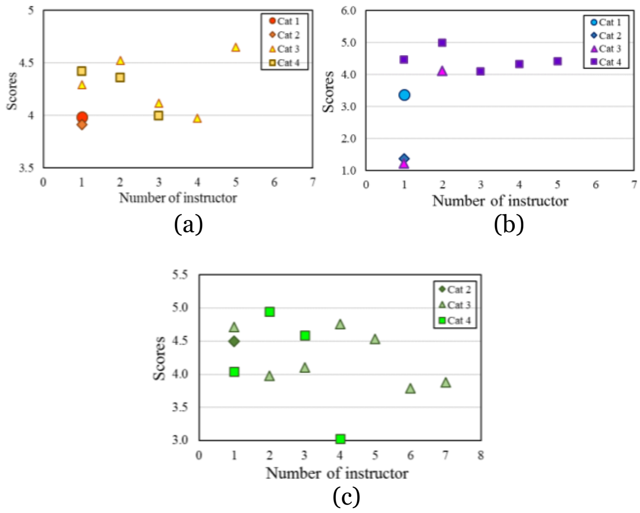


Figure 11. The TVET instructors Ability Map score mean for the Ability Map assessment without year of working experience for Course (a) 1, (b) 2 and (c) 3

The Figure 12 highlights the assessment of instructor ability in teaching and technical competency without the influence of year of working experience across three courses, showing varying performance levels. Course 3 stands out with the highest mean score with 4.24 and maximum score of 4.9, reflecting overall excellence and strong instructor competency, though its minimum score of 3.3 suggests minor gaps to address. With a strong mean of 4.22 and a comparatively high minimum score of 3.5, Course 1 exhibit consistent performance, showing fewer shortcomings but still space for improvement to achieve the best attainable results. With the lowest mean of 4.08 and minimum score of 2.8, Course 2 on the other hand, exhibit the greatest variability, underscoring the disparities among TVET instructor. Targeted adjustments are required to support underperforming instructors and boost the overall performance, even though Course 2 receive a good maximum score of 4.7.

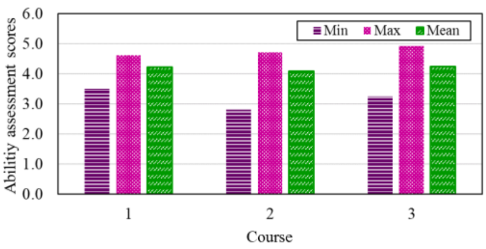


Figure 12. The TVET instructor ability assessment score without year of working experience

The Course 2 mean standard deviation for the Ability Map assessment without year of working experience is scattered above Course 1 and 3 between 1.2 and 1.6, as shown in Figure 13. The Course 1 and 3 mean standard deviation for the Ability Map assessment without year of working experience is quite similar whereby it is scattered between 0.4 and 1.

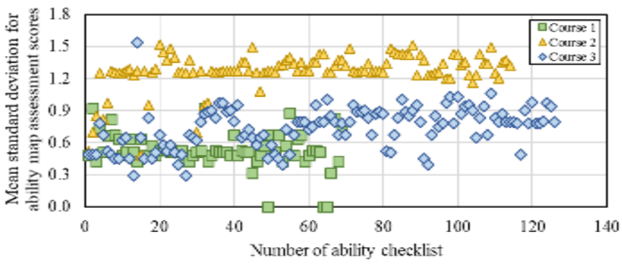


Figure 13. The standard deviation of Ability Map assessment without year of working experience

B. Neural Networks

For Course 1, FFNN achieved its highest and lowest regression value at 40 and 10 neurons, as seen in Figure 14(a). In contrast, CFNN presented mean regression for 5 sets of neurons without specific numerical values as shown in Figure 14(b). For Course 2, both FFNN and CFNN exhibited a range of regression values for Ability Map assessment with year of working experience between 0.839 and 0.84. Moving to Course 3, FFNN showcased a mean regression of 0.638 for Ability Map assessment with year of working experience, reaching its high point at 0.64 with 50 neurons. For Course 3, CFNN displayed similar regression values for Ability Map assessment with year of working experience, ranging from 0.64 for 10 to 30 neurons, with the lowest at 40 neurons, aligning closely with FFNN's performance.

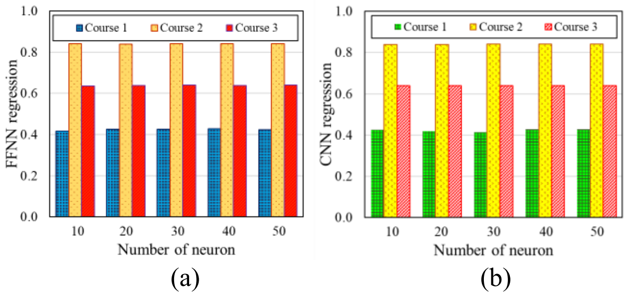


Figure 14. The Ability Map assessment with year of working experience regression based on (a) FFNN and (b) CFNN analysis

FFNN for Course 2 Ability Map assessment with year of working experience has a mean MSE of 0.663, reaching its minimum value of 0.609 with 50 neurons, as depicted in Figure 15(a). For Course 1, the MSE for Ability Map assessment with year of working experience falls within the range of 0.199 and 0.242. In the context of the Course 3, the lowest MSE for Ability Map assessment with year of working experience is attained with 20 neurons at 0.273, while the highest is recorded with 40 neurons at 0.489.

As for CFNN, the Course 1 mean MSE for Ability Map assessment with year of working experience stands at 0.274, and the lowest values are observed for 40 and 50 neurons at 0.272, as illustrated in Figure 15(b). The Course 2 MSE for Ability Map assessment with year of working experience varies between 0.668 and 0.674. In contrast, Course 1 achieves its lowest highest MSE is observed at 30 neurons with a value of 0.276.

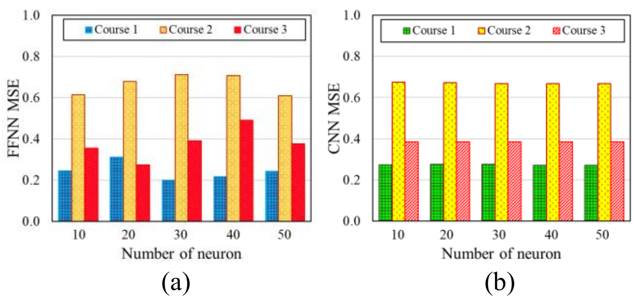


Figure 15. The Ability Map assessment with year of working experience MSE based on (a) FFNN and (b) CFNN analysis

In this study, the analysis for the FFNN and CFNN is performed on the best number of neurons analysed. According to the FFNN, the best number of neurons for Course 1, 2 and 3 is 40, 50, and 20, respectively. As for the

CFNN computation, the best number of neurons is 50, 30, and 20 for Course 1, 2 and 3, respectively.

The influence of year of working experience as a factor in TVET instructor competency assessment using FFNN and CFNN models, compared to the Ability Map method, showed varying impacts across CAT 1 to 4 for Courses 1, 2, and 3. For Course 1, the results across all categories were closely aligned, indicating minimal influence of year of working experience as seen in Figure 16. In CAT 1, the Ability Map recorded a mean of 3.9855, while FFNN and CFNN showed slight decreases at 3.9848 and 3.9581, respectively. Similarly, in CAT 2, the Ability Map had 3.9130, whereas FFNN and CFNN dropped slightly to 3.8623 and 3.8846. For CAT 3, FFNN value is 4.3099 and CFNN is 4.3224, which almost identical to the Ability Map at 4.3101. Lastly, in CAT 4, FFNN recorded 4.2326 and CFNN 4.2752, both slightly lower than the Ability Map value of 4.2609.

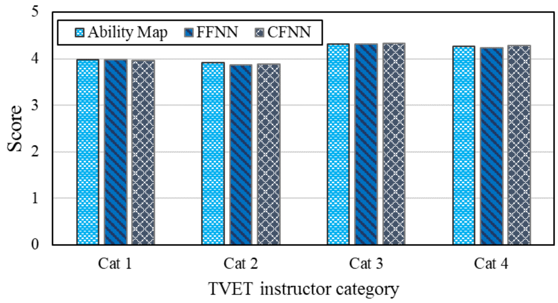


Figure 16. The mean score for year of working experience influence on the Course 1 based on Ability Map assessment and NN analysis

For Course 2, the impact of year of working experience was more notable, particularly in CAT 1 and 4 as shown in Figure 17. In CAT 1, the Ability Map mean was 3.3772, while FFNN increased slightly to 3.4607, and CFNN to 3.4234, indicating a small positive impact. In CAT 2, however, the Ability Map value of 1.3772 remained largely consistent with FFNN at 1.3457 and CFNN at 1.4370, showing mixed results. In CAT 3, the Ability Map recorded for 3.7632, with FFNN increasing marginally to 3.7813, while CFNN decreased slightly to 3.7442. For CAT 4, FFNN value is 4.4893 and CFNN is 4.4805, showed small increases compared to the Ability Map with 4.4649, demonstrating a subtle improvement when incorporating year of working experience.

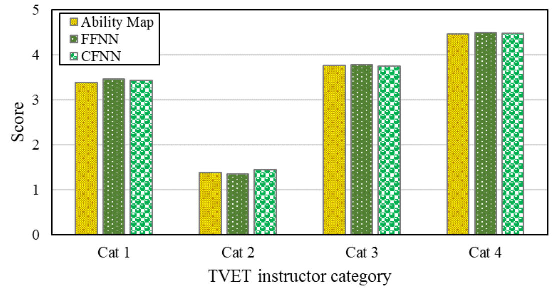


Figure 17. The mean score for year of working experience influence on the Course 2 based on Ability Map assessment and NN analysis

For Course 3, year of working experience had minimal influence across categories, particularly in CAT 2 and 3. In CAT 1, all methods recorded a value of 0, showing no change as seen in Figure 18. In CAT 2, the Ability Map value of 4.5 remained consistent, with FFNN at 4.4999 and CFNN at 4.4939, showing negligible differences. Similarly, in CAT 3, the Ability Map had 4.2517, compared to FFNN at 4.2356 and CFNN at 4.2452, reflecting very slight variations. In CAT 4, FFNN (4.1784) and CFNN (4.1571) were marginally higher and lower, respectively, than the Ability Map mean of 4.1488, indicating small shifts.

While the influence of year or working experience through FFNN and CFNN produced improvements in specific categories of CAT 1 and 4 for Course 2, the overall impact across all courses and categories was seen, with most variations can be visualised. This suggests that year of working experience refines the assessment results and can improve the competency assessment.

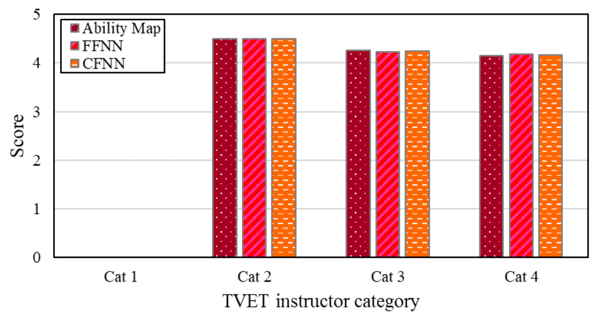


Figure 18. The mean score for year of working experience influence on the Course 3 TVET based on Ability Map assessment and NN analysis

Specifically, for Course 1, the FFNN analysis suggests that the Ability Map scores of 5 instructors should be lower than the current results by Ability Map. On the other hand, the CFNN analysis indicates that the scores for 3 TVET instructors based on the Ability Map assessment with year of working experience should be higher than the current scores computed by the Ability Map assessment without year of working experience.

In the case of Course 2, the FFNN analysis reveals that 4 TVET instructors, including 1 from CAT 2 and 3, and 2 from CAT 4, should obtain higher Ability Map scores. Conversely, the CFNN analysis suggests that 2 TVET instructors from CAT 3 and 4 are expected to receive lower scores, while 2 TVET instructors from CAT 2 and 4 are projected to receive higher scores.

For Course 3, FFNN and CFNN analysis shows that the score for TVET instructors under CAT 4 should be lower than the currents scores by Ability Map. FFNN and CFNN also found that the score for TVET instructor under CAT 2 and 3 are approximately parallel with Ability Map assessment without year of working experience.

The influence of year of working experience in Ability Map assessment differs significantly between FFNN and CFNN across the three courses as seen in Table 4. FFNN shows a higher mean influence in Course 2 at 5.47% compared to 0.33% in Course 1 and 0.52% in Course 3, with high variability, particularly in Course 3 where the standard deviation reaches 63.81%. On the other hand, CFNN displays a slightly higher mean influence for Course 2 at 5.78%, but much lower mean in Course 1 at 0.20% and Course 3 at 0.04%, along with more consistent results as seen in the lower standard deviation for Course 3 at 27.38%. This indicates that FFNN have greater variability, while CFNN demonstrates consistency in its assessments.

Table 4. The percentage for influence of the year of working experience in Ability Map assessment

NN method	Mean (%)			Standard deviation (%)		
	Course					
	1	2	3	1	2	3
FFNN	0.33	5.47	0.52	51.13	5.26	63.81
CFNN	0.20	5.78	0.04	46.48	3.75	27.38

IV. CONCLUSION

In this study, TNA based on a combination of the Ability Map developed using the CUDBAS method and the backpropagation NN technique was performed to analyse the influence of TVET instructor year of working experience on Ability Map assessment scoring. The percentage of regression for FFNN is almost similar to CFNN for analysis on Courses 1 and 2, while for Course 3, FFNN is 0.2% higher than CFNN. The higher percentage difference in MSE between FFNN and CFNN is found in the Course 1 analysis, where CFNN is 11.4% higher than FFNN. For the percentage of MSE on Courses 2 and 3, the value of FFNN is still lower than CFNN, with 1.01% and 2.25%, respectively. FFNN and CFNN analyses reveal varying percentage mean differences and standard deviations, with FFNN generally indicating higher impacts of the TVET instructor profile on year of working experience in certain courses, particularly Courses 1 and 3. For Course 2, FFNN and CFNN achieved regression values ranging between 0.839 and 0.84, indicating high predictive accuracy, while the Ability Map method does not explicitly offer regression-based evaluation. FFNN and CFNN also demonstrate performance with lower MSE values. This can be found for Course 2 where CAT 1 scores increased from 3.3772 based on Ability Map to 3.4607 and 3.4234 using FFNN and CFNN, respectively. FFNN and CFNN visualise performance variations more effectively, enabling targeted improvements. FFNN and CFNN leverage machine learning to model nonlinear relationships and improve predictive accuracy, compared to the static calculations of the Ability Map. FFNN and CFNN offer data-driven adaptability that evolves with the Ability Map assessment scores, enabling more nuanced and individualised performance assessment. This makes neural networks can be used to enhance competency assessment that are requiring continuous improvement and evaluation.

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VI. AUTHORS CONTRIBUTION

Conceptualisation, A.H. Mohd Hashim and M.F. Kamaruddin; methodology, A.H. Mohd Hashim and M.F. Kamaruddin; validation, A.H. Mohd Hashim, M.F. Kamaruddin, N. Sahimi and S. Mohd Sharif; resources, N. Sahimi and S. Mohd Sharif; writing—original draft preparation, A.H. Mohd Hashim and M.F. Kamaruddin; writing—review and editing, A.H. Mohd Hashim, M.F. Kamaruddin, N. Azis, J. Jasni, M.A. Mohd Radzi, and N.A. Ismail; All authors have read and agreed to the published version of the manuscript.

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