Eng Int Syst (2026) 2: 245–259

Engineering
Intelligent Systems

Instructor-Centered Education and Performance in Vocational Education for the Digital Economy Using the Fuzzy Logic Algorithm

Min Li*

School of Marxism, Zhengzhou Railway Vocational and Technical College, Zhengzhou 451460, China

Vocational Education (VE) responses to the digital economy have recently improved based on instructor-centric education. The VE performance influencing the digital economy is improved using the instructor's knowledge and consistent assessments. To enhance the evaluation of VE performance, this article proposes an Instructor Skill-based Assessment Method (ISAM) using fuzzy logic (FL). This method analyzes the performance using instructor skills for improving the digital economy. First, the crisp inputs from the various instructor skills and experience factors are analyzed using different fuzzification levels. The levels are determined using the maximum output generated after each factor analysis. This encourages multiple-level outputs for preventing nullified assessments. These assessments are eliminated from the fuzzification process to reduce time complexity. The instructor knowledge update and skill improvements are recommended based on the avoidance count. This recommendation is intended to leverage the digital economy regardless of the instructor's experience. Therefore, the proposed method improves instructors' performance and the digital economy.

Keywords: digital economy, fuzzy logic, performance assessment, vocational education

1. INTRODUCTION

Instructor-centric vocational pedagogy is a traditional teaching method. The instructor-centric learning environment creates a familiar role in the classroom, providing the necessary knowledge to the students [1]. Many methods and techniques are used for the analysis of instructor-centric vocational education. An analysis of teacher-centred learning (TCL) is used to evaluate students' performance [2]. The TCL method uses circuit theory to gather the necessary performance range of students. The circuit theory identifies students' exact skill sets, knowledge levels, and communication skills during the vocational learning process. Hence, the circuit theory evaluates performance based on the overall skills of learners [3,4]. The TCL-based method increases the efficiency of the analysis, improving the systems' feasibility level. An importance-performance analysis (IPA) approach is used to evaluate the academic performance level of vocational education and training (VET) of students [5,6]. The IPA approach analyzes VET students' job search ability, employability, and key skills. The IPA method is used to analyze the job-hunting ability, employability and key skills of VET students, with the aim of identifying the key elements that affect students' career development performance. "Service" does not refer to commercial services, but rather the employment guidance services, vocational ability cultivation services, internship and job recommendation services, learning support services, and skills improvement services provided by the vocational education system and institutions to students. In the IPA analysis, these services are regarded as important components that influence students' employment outcomes. By identifying and classifying relevant data, the IPA method

*Corresponding author e-mail: limin_vip@outlook.com

can generate structured information in the analysis process, reducing the complexity of subsequent decision-making and project improvement stages. Based on the diagnostic results of IPA, institutions can identify the priority areas for improvement in career guidance, skills training, job matching and learning support, and enhance the overall service quality and performance of VET students in the entire education and employment support system [7].

The main purpose of the vocational education system is to give students the skills and knowledge they require for the workplace. Vocational education significantly impacts the digital economy by providing high-quality teaching services [8]. Vocational education increases students' employability by providing them with necessary practical skills while also increasing their active participation and employment opportunities [9]. The main aim of vocational education training is to develop students' overall skills. Give Attributes such as competency, self-efficacy, proactivity, and interaction skills are used for training evaluation [10]. The key components create a significant impact in digital platforms that develop the conceptual tasks of the applications. Vocational education also improves the safety and security of digital transactions, reducing economic development difficulties [11]. Vocational education reduces the unemployment ratio, which improves the financial status of individuals as well as society in general. Vocational education provides education based on students' preferences and priorities, which minimizes the difficulty of navigating employment systems [12].

Fuzzy-based analysis methods and techniques are used for the analysis of vocational education performance. The fuzzy-based analysis is used to reduce the problems in the computation process [13]. A fuzzy analysis technique is primarily used to evaluate the performance range of students in vocational education and training (VET) systems. The fuzzy analysis technique analyzes the characteristics and behavioral features of vocational learners. A comprehensive evaluation model is implemented that evaluates the actual features of the learners. The evaluation model improves the accuracy of performance analysis, providing feasible data to assist students' academic growth [14]. A fuzzy Delphi technique is also used for the analysis of VET systems' performance. The Delphi technique analyzes the knowledge and skill sets of students. The academic performance level of students is derived from their scores for various tests conducted during the training period. The Delphi technique provides essential data for the performance improvement process that enhances the competency of students [15, 16]. However, instructor-centered pedagogy in vocational training faces several difficulties because of the evolving technological landscape. In addition, the traditional approach cannot effectively determine students' employability, knowledge and current skills. The traditional approaches have few hands-on programs and there is limited student readiness. Moreover, digital-centric roles require a high level of experience and knowledge. Therefore, this study uses the various fuzzification level and vocational education assessment process to improve teaching recommendations. The following are the contributions of this article:

(1) An instructor skill-based vocational education assessment is designed to improve the digital economy's significant positive impact.

(2) It examines the implications of different fuzzification levels for handling nullified and recommendation-based suggestions based on instructor skills, making the process less complex.

(3) Using different metrics and processes, it performs a comparative analysis to verify the proposed method's efficiency.

2. RELATED WORKS

This section reviews the previous works of various authors, examining their focus, approaches, key areas of interest, and techniques. Abdullah et al. [17] employed a fuzzy Delphi technique to ascertain the essential components for implementing mobile learning, specifically emphasizing delivering pertinent learning services to learners. The researchers utilized competency-based education to enhance interview sessions, and the findings demonstrated that FDM improved the effectiveness of learning methodologies.

Delcker et al. [18] utilized a text-mining methodology to examine courses at vocational institutions. Their objective was to ascertain significant keywords throughout the courses. The utilization of digital capabilities improved the accuracy of the content analysis. Their methodology enhanced the precision of curricular content analysis.

Chukwuedo et al. [19] conducted a study to determine the occupational identity status within electrical technology education systems. Their objective was to improve students' belief in their ability to succeed, and their employment-seeking skills. Students were given career-focused practical skills training to improve their understanding of their own vocational abilities. The researcher's assistance strengthened the efficacy of pupils in vocational education training programs.

Chukwuedo et al. [20] created a direct learning model to investigate vocational education. They focussed on identifying the learners' commitments, employability skills, and decision-making knowledge. An explicit learning model was utilized to examine crucial parameters for subsequent procedures. Their methodology enhanced the comprehensive set of abilities possessed by students in terms of vocational education.

Huang et al. [21] applied STEAM teaching to upper vocational engineering students. Their objective was to enhance the efficacy of educational systems. The TAM algorithm model assessed the learning paths' validity and efficiency. The implementation of STEAM-based education improved the precision of decision-making procedures.

Calero López et al. [22] performed a bibliometric analysis on vocational education and training (VET). The researchers examined the transversal competence and soft skills of VET students. An analysis was conducted on transversal competency to enhance pupils' employability prospects. Their work optimized the practicality of VET systems.

Dogara et al. [23] introduced a conceptual framework for work-based learning (WBL) in vocational and technical education systems. They devised a mechanism for random sampling to ensure pupils' adequate preparation for the workforce. The influence of interpersonal skills was identified in the process of technical advancement. Their structure offered adequate and appropriate services to learners in vocational and technical education systems.

Conejero et al. proposed a data-driven decision-making method for vocational and educational training (VET) [24]. The proposed method is a multicriteria method that assesses the criteria influences in VET. Both worst and best scenarios are analyzed, producing optimal information for the decision-making process. The proposed method improves decision-making accuracy, enhancing the reliability of the VET systems.

Zwart et al. proposed a new digital learning material (DLM) impact detection method for vocational education [25]. The method's main aim is to identify learners' self-efficacy features. DLM features are used to improve the self-learning abilities of students. DLM gives students the appropriate mathematical skills required to expedite computations. The proposed method reduces the latency in impact detection, enhancing the robustness of vocational education systems.

Romero-Gázquez et al. developed a European training action IN4WOOD for academic and business education systems [26]. A new training tool is used in the model to train the students based on preference and soft skills. The students are trained to use key technologies to increase their employability when job searching. The training tool also evaluates students' knowledge levels, reducing the systems' complexity. The developed model improves the performance and effectiveness of education systems. Similarly, Pei et al. proposed a deep learning (DL) based intelligent educational evaluation method for online education systems [27]. The researchers apply the DL algorithm to classify the types of learning problems, thereby producing relevant data for the evaluation process. The DL algorithm uses offset the minimal sum (OMS) method to reduce the computational cost. The proposed method increases the performance level of online learning systems.

Chukwuedo et al. designed a new influence detection method for vocational education systems [28]. The method's actual goal is to detect students' self-directed learning abilities. Students' lifelong learning tendencies and study engagement interests are improved using the detection method. The detection method reduces the identification latency, reducing the complexity of learning systems. The designed method improves the academic performance and well-being range among students.

Wu et al. introduced a new machine learning (ML) technology for secretarial pedagogy [29]. A Bayesian optimization algorithm is used to analyze the optimal parameters for the teaching process. The optimization algorithm increases the speed and accuracy with which learning services are provided to the students. The ML technique reduces the time consumption in training systems. The proposed ML technique enhances the development level of teaching systems.

In recent years, significant progress has been made in improving Vocational Education (VE) responses to the digital economy. This improvement has been achieved by implementing instructor-centric education, which focuses on harnessing instructors' knowledge and expertise and using consistent assessments. VE performance has been enhanced by leveraging the instructor's skills and experience, positively impacting the digital economy. However, there is a need to further strengthen the evaluation of VE performance and address this issue. According to the studies conducted by various researchers, traditional techniques face difficulties because of the outdated curriculum, indicating that instructors need to update their skills and curriculum activities frequently to improve their teaching methods. As aforementioned, the traditional teaching methods offer little opportunity for hand-on learning, which makes it difficult to identify the digital economy role. Also, the lecture-based teaching approach causes students to be passive learners with minimal engagement and poor knowledge retention. Traditional research and teaching practices find it difficult to make timely adjustments in accordance with the differences in learning speeds and individualized needs among students. Teachers' attention time and intervention opportunities in the classroom are limited, and the personalized guidance and problem-solving support they can provide are insufficient, which significantly restricts the overall performance of the teaching system in responding to student differences and improving learning outcomes.. Therefore, this study proposes the Instructor Skill-Based Assessment Method (ISAM) Using Fuzzy Logic (FL) to address the shortcomings of previous research. The detailed working process of ISAM-FL is described in the next section.

3. PROPOSED METHODOLOGY

3.1 Instructor Skill-Based Assessment Method (ISAM) Using Fuzzy Logic (FL)

This study introduces a novel approach called the Instructor Skill-based Assessment Method (ISAM) using fuzzy logic (FL). The main objective of ISAM is to analyze VE performance by considering the instructor's skills and their influence on the digital economy. The method begins with an analysis of the crisp inputs derived from different instructor skills and experience factors to achieve this. These inputs are then subjected to analysis using various fuzzification levels. These levels are determined based on the maximum output generated after each factor analysis. The purpose of employing multiple fuzzification levels is to encourage the generation of multiple-level outputs, thereby avoiding nullified assessments. By preventing nullified assessments, valuable insights are retained, ensuring a more accurate evaluation of VE performance.

Moreover, this approach saves a significant amount of time by excluding nullified assessments from the fuzzification process. ISAM goes beyond evaluation by utilizing the count of avoided nullified assessments to provide recommendations for instructor knowledge updates and skill improvements. This recommendation mechanism benefits the digital economy, regardless of the instructor's experience level. By identifying areas where instructors may need to update their knowledge or enhance their skills, the method ensures that VE effectively contributes to the digital economy. Figure 1 depicts the proposed ISAM-FL working process.

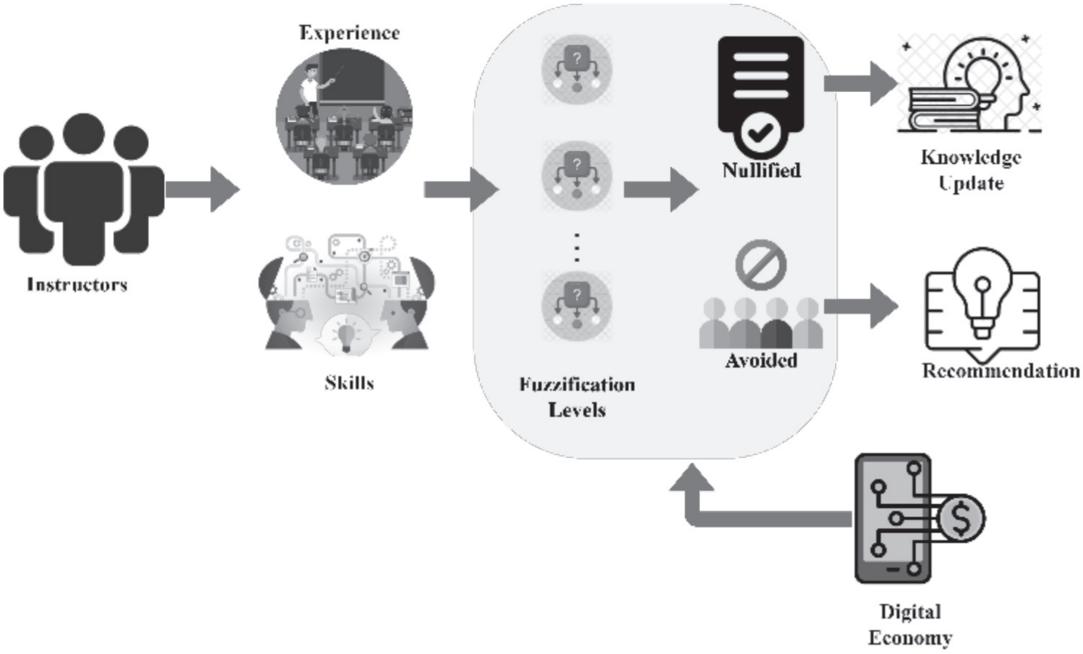


Figure 1 Proposed ISAM-FL working process.

In vocational education training, instructors are closely observed to identify and extract their unique skills and experience. These observations serve as the crisp inputs, representing the concrete and specific data utilized in the fuzzification process. Fuzzification involves converting these crisp inputs into linguistic variables or fuzzy sets, allowing for a more flexible and nuanced analysis of the instructor's performance. By employing fuzzification, the evaluation process captures the intricacies of instructor skills and experiences, enabling a more comprehensive and accurate assessment of their capabilities in vocational education. The method of observing the instructors in order to determine their level of knowledge and skills is given in Equation (1):

$$\left.\begin{aligned}
&\rho(x) = \begin{cases} 1 & \text{if } x = n \\ 0 & \text{if } x \neq n \end{cases} \\
&\qquad \rho{:}n \to x \\
&\rho_x(X) = \begin{cases} \rho(x) & \text{if } \rho^{-1}(x) \neq 0 \\ 0 & if\ \rho^{-1}(x) = 0 \end{cases} \\
&\qquad \rho{:}n \times n \to N \\
&(x, y) \to \rho(x, y) = x * y \\
&\rho(x) = \begin{cases} [\rho(x)\Delta\rho(y)] & \text{if } \rho^{-1}(x) \neq 0 \\ 0 & \text{if } \rho^{-1}(x) = 0 \end{cases}
\end{aligned}\right\} \tag{1}$$

Where ρ represents the observation operation of the instructors, x denotes the input verification from the instructors, y is the efficaciousness of the obtained instructors. Then the experience and skills are extracted for further fuzzification. In vocational education training, extracting experience from instructors being observed is crucial in determining the fuzzification levels. When instructors are observed, their accumulated experience and expertise are identified and considered valuable input for the fuzzification process. This experience is diverse, ranging from practical industry knowledge to teaching methodologies and problem-solving skills. By extracting and analyzing this experience, the fuzzification levels are determined based on the richness and depth of the observed instructor's expertise. This ensures that the fuzzification process adequately captures the nuances and complexities of their experience, allowing for a more refined and accurate assessment of their performance in vocational education. Equation (2) is used to extract the expertise of the instructors:

$$\left.\begin{aligned}
&D_x = x * y \\
&D(\overline{X}, \overline{Y}) = \overline{\rho} \\
&D(X, Y) = \rho_n \\
&x = \rho(x, y) \\
&\overline{X} = \rho(\tilde{n}, \tilde{y}) \\
&X_n = [\underline{X}(n), \overline{X}(n)] \\
&X_n = \{\tfrac{x}{n} = \rho(x, y)\}
\end{aligned}\right\} \tag{2}$$

Where D represents the experience of the instructors. The input verification (x) and the efficaciousness (y) determine the experience of the instructors $(D_x = x * y)$. Then the skills of the instructors are determined for further fuzzification levels. In vocational education, extracting instructors' skills is vital in determining the subsequent fuzzification levels. When extracting instructors' skills, their specific capabilities, competencies, and proficiencies relevant to vocational training are identified and assessed. These skills encompass various areas comprising technical expertise, instructional abilities, communication skills, and problem-solving capabilities. The extracted skills serve as the foundation for establishing the fuzzification levels, which are determined. This allows for a more delicate and precise fuzzification process, enabling a comprehensive evaluation of instructors' skills and their

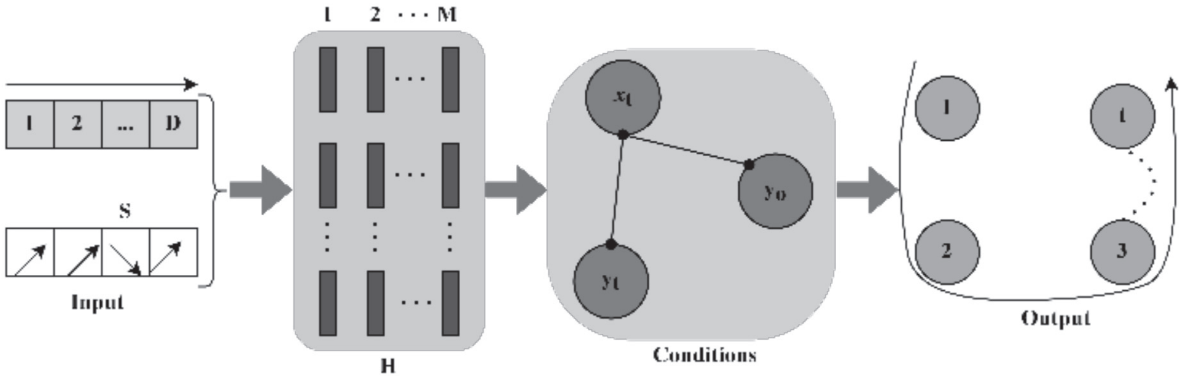


Figure 2 Fuzzification process using experience and skills.

potential impact on vocational education. Equation (3) is used to derive the skills of the instructors:

$$\left.\begin{aligned} &S_t = n_t \\ &x.y_t = n \cdot (y_t - y_{t-1}) \\ &(y - n) \cdot y_t = n.y_{t-1} \\ &y_t = \left(\frac{y}{y-n}\right).y_{n-1} \\ &y_t = \left(\frac{y}{y-x}\right)^t \\ &y_0 = \left(1 + \frac{x}{y-x}\right)^t \\ &y_{0.t} = \left(\frac{y}{y-x}\right)^t \cdot \left(1 + \frac{x}{y-x}\right)^t \end{aligned}\right\} \tag{3}$$

Where S is represented as the instructors' skills, t is denoted as the competencies of the instructors. These factors are the crisp inputs to the fuzzification levels operation to identify the invalid and avoided outputs from the assessments. In vocational education training, the fuzzification process involves assigning fuzzy sets to the crisp inputs of instructors' experience and skills. These fuzzification levels are determined by analyzing the instructors' expertise and proficiencies. Fuzzy logic transforms the crisp inputs into linguistic terms, enabling a more flexible and refined representation. The fuzzification levels capture the varying degrees of instructors' experiences and skills, enabling a more comprehensive evaluation of their performance. This approach provides a deeper understanding of instructors' capabilities and helps assess their suitability for different aspects of vocational education training. The process of fuzzification by using crisp inputs such as the experience and skills of the instructors is explained by Equation (4):

$$\left.\begin{aligned} &H = \frac{x}{y-x} \\ &x(y_t - y_{t-1}) = \frac{x}{y} \\ &\text{where } t = 1, 2, \ldots, n \\ &H_t - H_{t-1} = \frac{x}{y} \\ &H_t \to \left(1 - \frac{x}{y}\right) \cdot H_t \\ &H_t = H_{t-1} \\ &= \left(\frac{y}{y-x}\right) \end{aligned}\right\} \tag{4}$$

Where H denotes the fuzzification process with the crisp inputs. The fuzzification process is carried out first by assessing the **effectiveness of the learner's performance**, and subsequently by conducting **operations that verify the learner's skill levels**, thereby generating the fuzzy representations required for this method $\left(H = \frac{x}{y-x}\right)$.

Based on the assessment results, the fuzzification process estimates the factors at different fuzzification levels. In analyzing instructor skills and experience factors, the crisp inputs are the precise data points obtained from these factors. Figure 2 presents the fuzzification process applied to experience and skills.

The H process is used for (D, S) in administering $S_t = n_t$; this is applied for all M. In this process $D(X, Y)$ is validated for ρ_n across multiple counts of ρ. This calculation is used to imply different conditions concerning (x_t, y_t) or (x_t, y_o) combinations. Therefore, if $x(y_t - y_{t-1}) = \frac{x}{y}$ is satisfied, then t is extracted (as high) from the instances. Thus M outputs are differentiated for t provided the conditions are satisfied until μ_t (Figure 2). To incorporate uncertainty and variability, fuzzification levels are applied. Fuzzification involves converting the crisp inputs into fuzzy sets, representing each input's degree of membership or relevance to different categories or levels. The nuances and gradations of the instructor's skills and experience factors are captured by utilizing different fuzzification levels, allowing for a more comprehensive analysis and understanding of their impact. The process of extorting the factors using different fuzzification levels is set out in Equation (5):

$$\left.\begin{aligned} &H_t = \left(\frac{y}{y-x}\right)^t \\ &H_0 = \left(1 + \frac{x}{y-x}\right)^t \\ &\text{where } t = 1, 2, \ldots, n \\ &\overline{y}_t = \left(\frac{\overline{y}}{\overline{y-x}}\right).y_0 \\ &\tilde{M} = \left(\frac{y}{y-x}\right) \\ &\tilde{M}_t = \left(\frac{y_t}{y_t - x_n}\right) \\ &\tilde{M}_t - N_n = \frac{y_t(N)}{y_t(N) - x_n(t)} \end{aligned}\right\} \tag{5}$$

M represents the different fuzzification levels. The factors and the evaluation outputs determine invalid and avoided assessments. Nullified assessment means eliminating or invalidating a performance assessment in vocational education

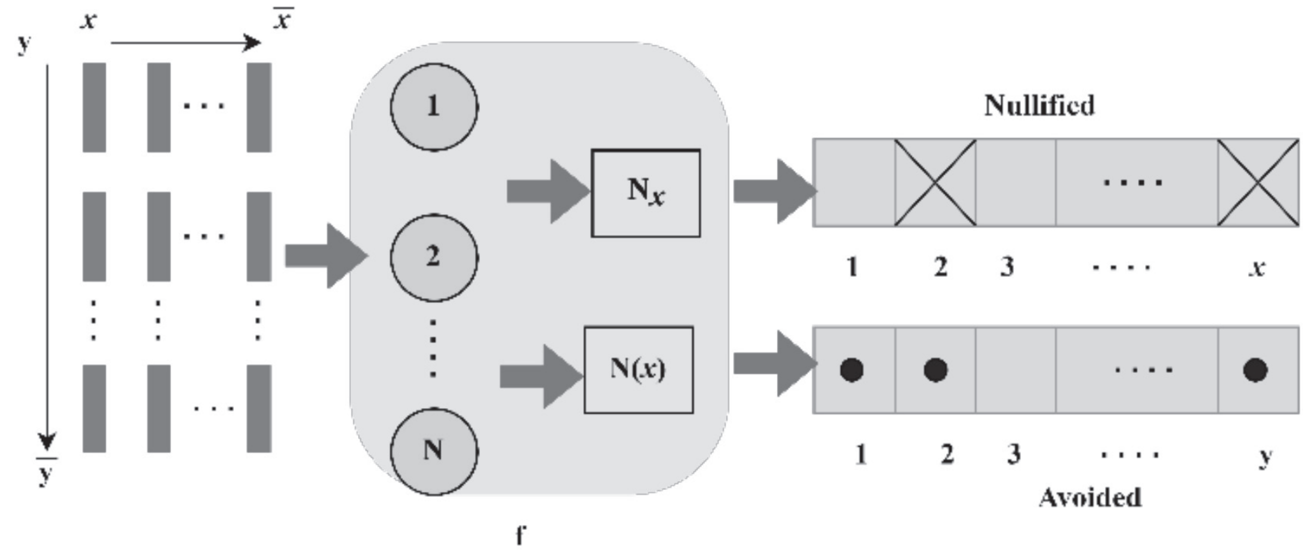


Figure 3 Nullified and avoided assessment classification.

and training. This occurs after fuzzification, which involves converting precise or crisp input data into linguistic terms or fuzzy sets. In nullified assessment, the evaluation or measurement of performance is disregarded or considered void for various reasons such as inconsistencies, biases, or inadequacies in the assessment process. It indicates that the assessment results are deemed unreliable or unrepresentative and, therefore, cannot be used to make accurate judgments or decisions about an individual's performance in vocational training. The process of determining the nullified assessments after the fuzzification process is explained by Equation (6):

$$\left.\begin{array}{l} \underline{K}(x) = f(\underline{x}, \overline{y}) \\ = \frac{\overline{y}(n)}{\overline{y}(n) - \underline{x}(n)} \\ \overline{K}(x) = f(\overline{x}, \underline{y}) \\ = \frac{\underline{y}(n)}{\underline{y}(n) - \overline{x}(n)} \\ f(x, y) = \frac{y}{(y - x)} \\ \left(\frac{\partial f}{\partial x} > 0\right) \\ \left(\frac{\partial f}{\partial y} < 0\right) \end{array}\right\} \tag{6}$$

Where K is denoted as the nullified assessments, f is represented as the output of the fuzzification process. This is considered an invalid assessment if no impacts are due to the obtained factors. Nullified assessments refer to evaluations or tests in vocational training deemed invalid or inconclusive due to the lack of effects from the measured factors. Typically intended to influence or enhance performance, these factors have shown no discernible impact on the trainees' abilities or outcomes. Consequently, the assessments become meaningless as they fail to reflect the trainees' true skills or progress accurately. This highlights the need to reevaluate the effectiveness of the factors being considered and potentially revise the training methods to ensure meaningful assessments in the future. The process for determining whether or not the nullified assessment has impacts due to the obtained factors is explained by Equation (7):

$$\left.\begin{array}{l} L_x \subseteq L_y; \\ N = 1 + \frac{x}{y - x} \\ \overline{N} = 1 + \frac{\overline{x}}{\overline{y} - \overline{x}} \\ N_x = [\underline{N}(x), \overline{N}(x)] \\ \underline{N}(x) = \frac{1 + \underline{x}(n)}{\overline{y}(n) - \underline{x}(n)} \\ \overline{N}(x) = \frac{1 + \overline{x}(n)}{\underline{y}(n) - \overline{x}(n)} \end{array}\right\} \tag{7}$$

Where L denotes the impact estimation on the invalid assessment, which is avoided after the fuzzification levels take place. Avoided assessment is a concept that relates to the impact of fuzzification levels on vocational training. Fuzzification is the process whereby crisp or discrete values are converted into fuzzy or continuous values. In the context of vocational training, fuzzification levels are used to determine the degree of subjectivity or flexibility in assessing learners' performance. The invalid and avoided assessment classification process is illustrated in Figure 3.

The combinations $(x, \overline{x})$ and $(y, \overline{y})$ are the inputs used for the f process throughout N. In this case N_x and $N(x)$ are the differential considerations for $L_x \subseteq L_{yi}$ for which x and y are independently analyzed. This is required for identifying nullified and avoided instances for which the two conditions are investigated. The conditions follow $\left(\frac{\partial f}{\partial x} > 0\right)$ and $\left(\frac{\partial f}{\partial x} < 0\right)$ for differentiating the n nullified and avoided classification. Post this classification process; the f is trimmed for matching $(y_t)_n$ and thus the following recommendation/knowledge updates are performed (Figure 3). By incorporating fuzzification, a vocational training program avoids rigid assessments and creates an adaptable learning environment. This approach recognizes learners' diverse abilities and skills, enabling personalized evaluation that considers individual strengths and weaknesses.

$$\left.\begin{array}{l} J_t = \overline{M}.y_0 \\ where\ t = 1, 2, \ldots, n \\ \rho(x) = \rho_m\left(\frac{x}{y_0}\right) \\ = \rho_m\left[\left(\frac{x}{y_0}\right)^{1/t}\right] \\ (y_t)n = \left[\frac{(y(x)).y_0}{(\overline{y}(x)-\underline{x}(n))}\right] \\ = [(\underline{M}(x))^t, (\overline{M}(x))^t] \end{array}\right\} \quad (8)$$

Avoided assessment based on fuzzification levels promotes a more comprehensive and fair evaluation system, fostering continuous improvement and better outcomes for vocational trainees. Equation (8) above is used to identify avoided assessments. Based on the impact of the digital economy, the avoided evaluation is determined using the fuzzification levels outputs. The determination of avoided assessment based on the impact of the digital economy in vocational training involves recognizing the transformative effect of digital technologies on the learning process. With the rise of the digital economy, a vocational training program leverages the resources to assess learners' skills and knowledge more effectively. This means that traditional assessment methods, that may be outdated or inadequately capture the dynamic nature of digital skills, do not have to be applied. By adopting digital tools for assessment, vocational training is better aligned with the digital economy's demands. The identification of the avoided assessment depending on the digital economy impact is obtained with Equation (9):

$$\left.\begin{array}{l} \tilde{B} = \frac{\overline{x}}{\overline{y}-\overline{x}} \\ B_n = [\underline{B}(n), \overline{B}(n)] \\ = \left[\frac{\underline{x}(n)}{\overline{y}(n)-x(n)}, \frac{\overline{x}(n)}{\overline{y}(n)-x(n)}\right] \\ H_t = \overline{M}.y_0 \\ \overline{H}_0 = \overline{x}\cdot y_0 \\ \rho H_0(x) = \rho_n\left(\frac{x}{y_0}\right) \end{array}\right\} \quad (9)$$

Where B represents the digital economy impact to estimate the avoided assessment after the fuzzification level operations. Then, the knowledge update is determined after the fuzzification levels and also based on the avoidance count, the knowledge update and recommendations are identified. In vocational training, the determination of knowledge update is influenced by the avoidance count, which refers to the number of instances where learners skip specific learning modules or activities based on their existing knowledge and skills. This approach acknowledges that individuals entering vocational programs may already possess relevant expertise or prior learning. By considering the avoidance count, vocational training can tailor the curriculum to meet the specific needs of each learner. This enables efficient knowledge updates by focusing on areas requiring improvement or expansion, optimizing the learning experience, and ensuring that learners acquire the most relevant and up-to-date skills. The enhanced knowledge update in vocational training is achieved by applying the fuzzification process. Fuzzification enables a more nuanced and flexible assessment of learners' knowledge, facilitating targeted updates and personalized learning experiences to meet individual needs and adapt to changing demands in the vocational field. The Vázquez knowledge update is estimated using Equations (10) and (11):

$$\left.\begin{array}{l} P(x) = \begin{cases} 0 & \text{if } x < \frac{y_3}{y_3-x_1} \\ \frac{(y_3-x_1)x-y_3}{(y_3+y_2+x_2-x_1)} & \text{if } \frac{y_3}{y_3-x_1} \le x \le \frac{y_2}{y_2-x_2} \\ \frac{(y_1-x_3)x-y_1}{(y_2-y_1)(y_2-y_1+x_3)} & \text{if } \frac{y_2}{y_2-x_2} \le x \le \frac{y_1}{y_1-x_3} \\ 0 & \text{if } x > \frac{y_1}{y_1-x_3} \end{cases} \\ \rho_B(x) = \begin{cases} 0 & \text{if } x < \frac{x_1}{y_3-x_1} \\ \frac{(y_3-x_1)x-y_1}{(y_3-y_2+x_2-x_1)} & \text{if } \frac{x_1}{y_3-x_1} \le x \le \frac{y_2}{y_2} - x_2 \\ \frac{(x_3)-(y_1-x_3)x}{(y_2-y_1)(y_2-y_1+x_3)} & \text{if } \frac{x_2}{y_2-x_2} \le x \le \frac{x_3}{y_1-x_3} \\ 0 & \text{if } x > \frac{x_3}{y_1-x_3} \end{cases} \end{array}\right\} \quad (10)$$

$$\left.\begin{array}{l} Q(x,y,z)(\rho) = \begin{cases} 0 & \rho < x \\ \frac{\rho-x}{y-x} & x \le \rho \le y \\ \frac{z-x}{z-y} & y \le \rho \le z \\ 0 & x \ge z \end{cases} \\ Q(x,x,x,) = \begin{cases} 1 & \rho = x \\ 0 & \rho \ne x \end{cases} \\ Q(0,0,z)(\rho) = \begin{cases} 0 & x \in (0,z) \\ \frac{z-x}{z} & x \in (0,z) \end{cases} \end{array}\right\} \quad (11)$$

Where P denotes the knowledge update and Q represents the output of the null assessments. Now, the recommendations are established after the avoided assessments determination process. Provide suggestions for the upcoming vocational training based on the number of cases to be avoided. Targeted interventions are designed by analyzing the frequency of mistakes or areas where trainees struggle. These recommendations may include additional practice in challenging topics, personalized support, or revised teaching methods to address common pitfalls. The process of providing the recommendations to enhance future vocational training sessions is explained by Equation (12):

$$\left.\begin{array}{c} \begin{cases} \frac{dV_st}{dV} = G\times H - Q_i - Q_j \\ \frac{dV_sq}{dV} = G\times H - J_i - J_j \end{cases} \\ V_i = \frac{\sum_{i=1} V_{ij}}{N} \\ V = \frac{G^*j}{G^2 i} \\ = \frac{\sum_{i=1}\left(G_i - \frac{1}{2}n(J+1)\right)}{\sum_{n=1}(G-1)} \end{array}\right\} \quad (12)$$

Where V represents the recommendations and s denotes the suggested improvements in skills. The recommendation aims to harness the potential of the digital economy, benefiting both instructors and the overall digital ecosystem, irrespective of their level of experience. The process for recommendations and knowledge update is illustrated in Figure 4.

The classified outputs are used for analyzing B impact for validating Q. In this Q process, $Q(x,y,z)\ \forall\ Q(x,x,x)$ or $Q(0,0,z)\ \forall\ \rho$ is utilized. Therefore, if $Q = true$ for the first case, then the knowledge is updated, and

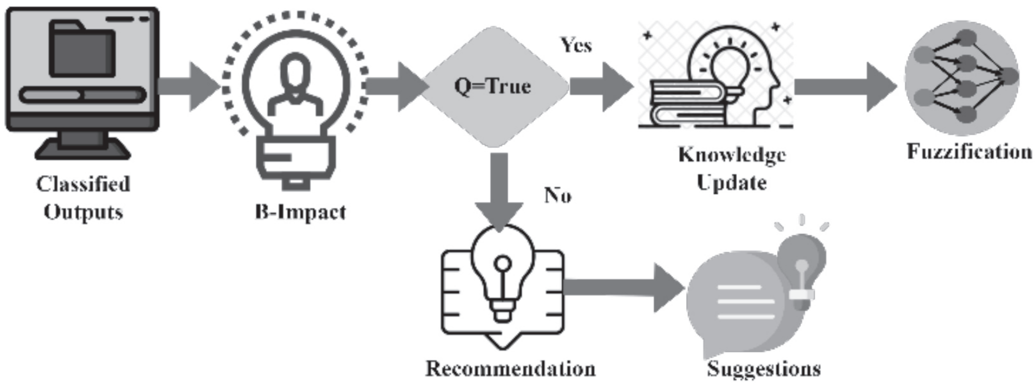


Figure 4 Recommendations and knowledge update process.

Table 1 Algorithm.

Initialize input x and efficaciousness y
For every instructor ρ,
Extract D using equation (2) // experience extraction
Extract S_t using equation (3) // skill extraction
Perform fuzzification operation H // change crisp value into fuzzification level
$D(X, Y)$ is validated for ρ_n across multiple counts of ρ
Extort the factors at different fuzzy level using equation (5)
Determine nullified assessment $\underline{K}(x)$ using equation (6)
recognizes learners' diverse abilities and skills using equation (8)
computed $\tilde{B}$ using equation (9)
update knowledge using equation (10 and 11)
Training session is initiated according to equation (12) and recommendations given.

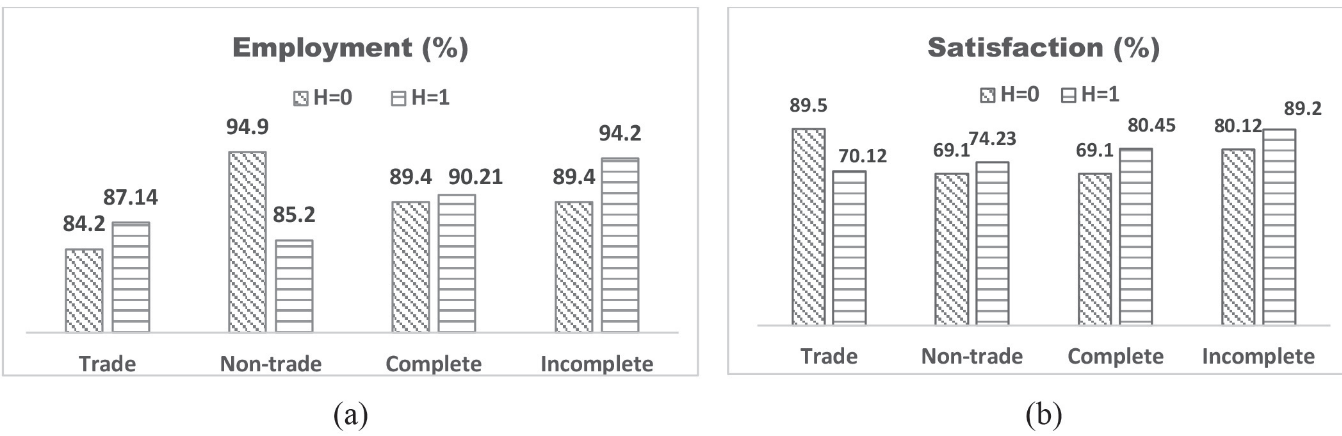
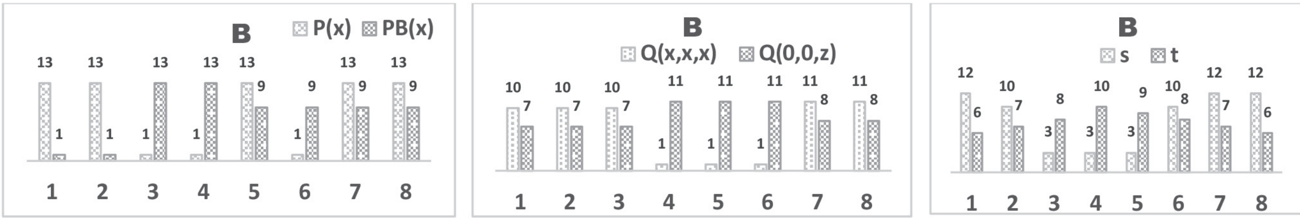


Figure 5 B Analysis.

further fuzzification is applied. The Q failing conditions are used for providing alternate recommendations with new suggestions (see Figure 4). This approach offers a twofold enhancement: first, it empowers instructors by providing them with opportunities to expand their reach and impact through digital platforms. Second, it contributes to the growth and advancement of the digital economy by creating a vibrant ecosystem that fosters innovation, collaboration, and economic prosperity. Effective vocational training is enhanced by implementing fuzzification techniques, which facilitate the precise assessment of individual skill levels and needs. The overall working algorithm is presented in Table 1.

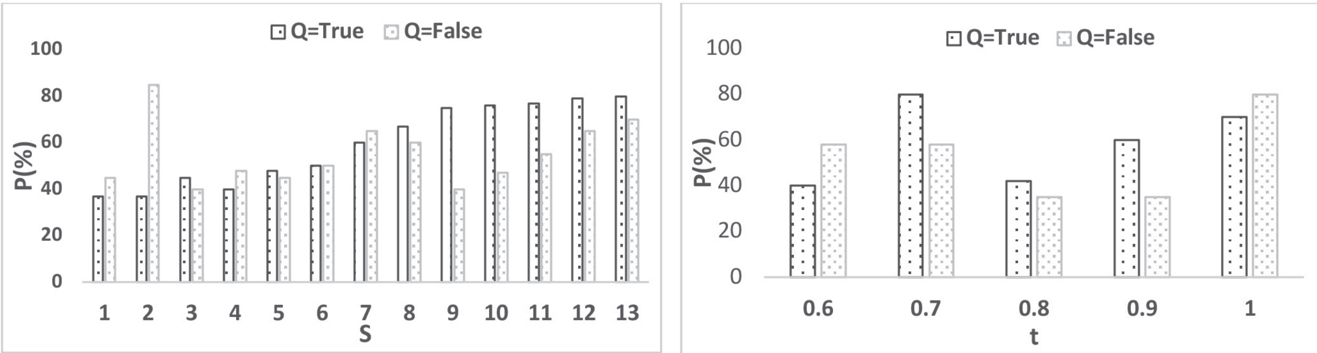
3.2 Data Analysis

The data analysis uses the information from (https://www.ncver.edu.au/ research-and-statistics/ visualisation- gallery/latest-vet-statistics) that confirms trainee and instructor data based on trade and non-trade placements. The data is accumulated from 2021, and various attributes such as employment and satisfaction ratios are analyzed. Specifically, the analysis is performed using 13 different skills and tutor experience of up to 8 years. Based on the information provided, the B analysis is performed in a step-by-step manner. The first analysis for B using employment and satisfaction is presented in Figure 5.



(a) (b) (c)

Figure 6 *B* Analysis.



(a) (b)

Figure 7 *P* Analysis $\forall(S, t)$.

The employment and satisfaction ratio due to B based on different fuzzification is shown in Figure 5. *Four* categories are analysed: trade, non-trade, completed, and incomplete VET courses. The $H = 0$ and $H = 1$ categories are presented based on before and after fuzzy processes. Thus, the change in f for $Q = True$ / $false$ is used for validating B's influence. Therefore, the recommendations based on previous knowledge updates and new fuzzification using (x, y) and $(\overline{x}, \overline{y})\forall\ f\ \in H$ is used to handle multiple $V \in T$ shortcomings, thus preventing difficulties (Figure 5). Based on the M, the analysis of B for $P(x)$ and $P_B(x)$ is handled as in Figure 6. In this analysis, the considerations are $Q(x, x, x)$ and $Q(, o, o, z)$ for the assessment of B.

The output generated based on multiple M (Here $M = 8$) is validated for different variants of $[P(x),\ P_B(x)],\ Q(x, x, x),\ A(o, o, z)]$, and (S, t). Therefore, the different conditions for $Q = True$ are satisfied across multiple f before L. If L is achieved in any case, the B reduction occurs; therefore, a new suggestion is prescribed. In the contrary case of (S, t), the associated skills or experience (at any point between $M = 1$ to 8) is utilized to mitigate such issues. Hence, the consecutive fuzzy increases the B impact for different employment and satisfaction levels (Figure 6). The generated outputs are based on t and S for the different training sessions. The training towards P and Q (mitigation) is the suggested improvement for consecutive f. The analysis for V in terms of t and S is presented in Figure 7.

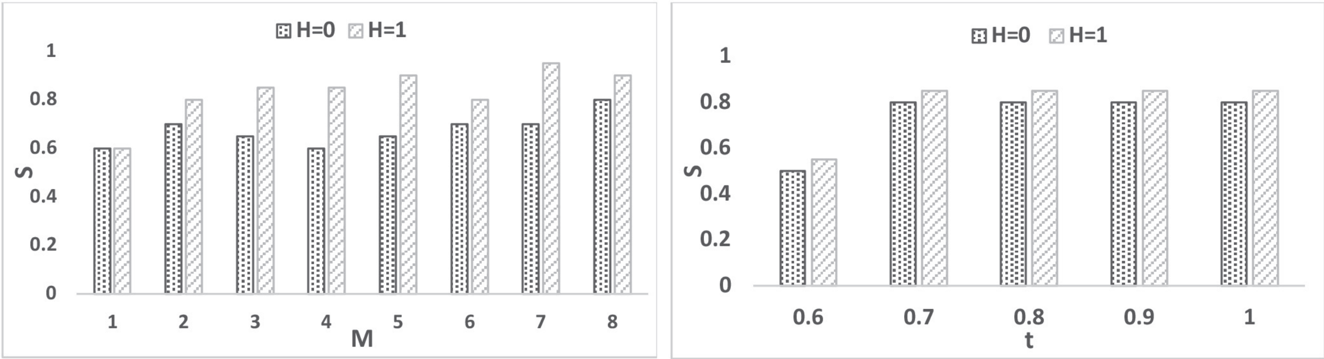
In Figure 7, the P analysis is performed based on $(S, t)\forall\ Q = true$ and $Q = false$ conditions. Based on the available $f\ \forall\ Q(o, o, z)$ and $Q(x, y, z)$ the Q mitigation is pursued. The above representation is contrary to distinguishable factors of $H \in \rho$ and $J_t = \overline{M}.y$. Therefore, the fuzzification for consecutive B is redeemed for improving multiple further recommendations. Thus, the $P(\%)$ is optimal with variations across $Q = True$ for S and t (Figure 7). For the purpose of analysis, the s for the varying μ and t is presented in Figure 8.

The analysis for s over the varying (M, t) is presented in Figure 8. The $H = 1$ and $H = 0$ cases show a massive variation for M , whereas it is less for t. This is due to the t and experience gained over the years. At some point, the s analysis is stabilized for different f satisfying Q. Thus, the derivatives $Q(x, x, x)$, $Q(o, o, z)$, and $(Q(x, o, o)$ are abruptly satisfied over the different iterations of fuzzy derivatives. Thus, the successive computations are achieved using multiple P for different M.

3.3 Comparative Study

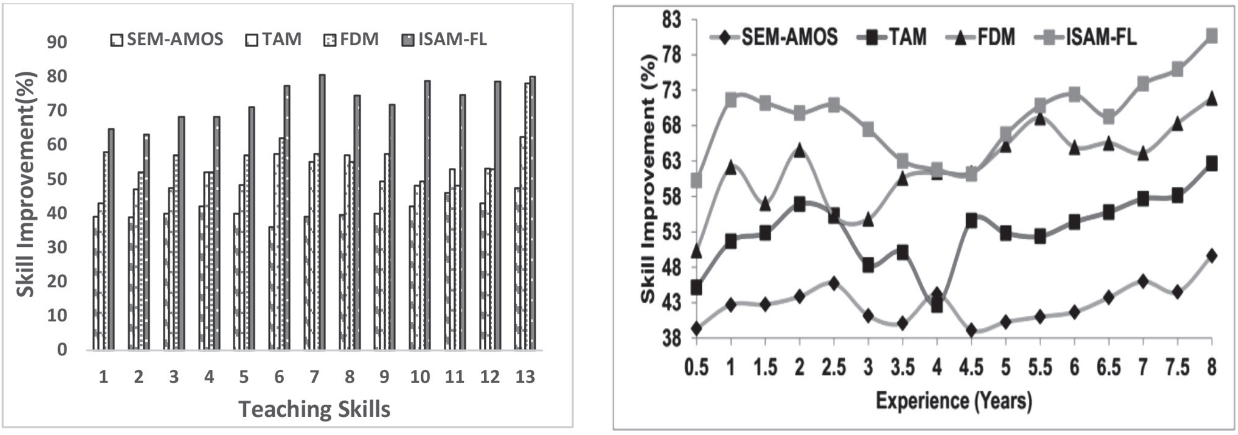
The comparative study uses skill improvement, recommendations, time complexity, recommendation accuracy, recommendation time, and output generated. The variables are the teaching skills and the experience. The methods SEM-AMOS [23], TAM [21], and FDM [17] have coincided with the proposed ISAM-FL in this study.

This method facilitates skill improvement by using the fuzzification process to enhance the efficiency of the vocational education training. In vocational training, fuzzification levels significantly contribute to effective skill improvement. By assigning fuzzy membership functions to different skill levels, trainers accurately assess and determine the proficiency



(a) (b)

Figure 8 s analysis $\forall\ (M, t)$.



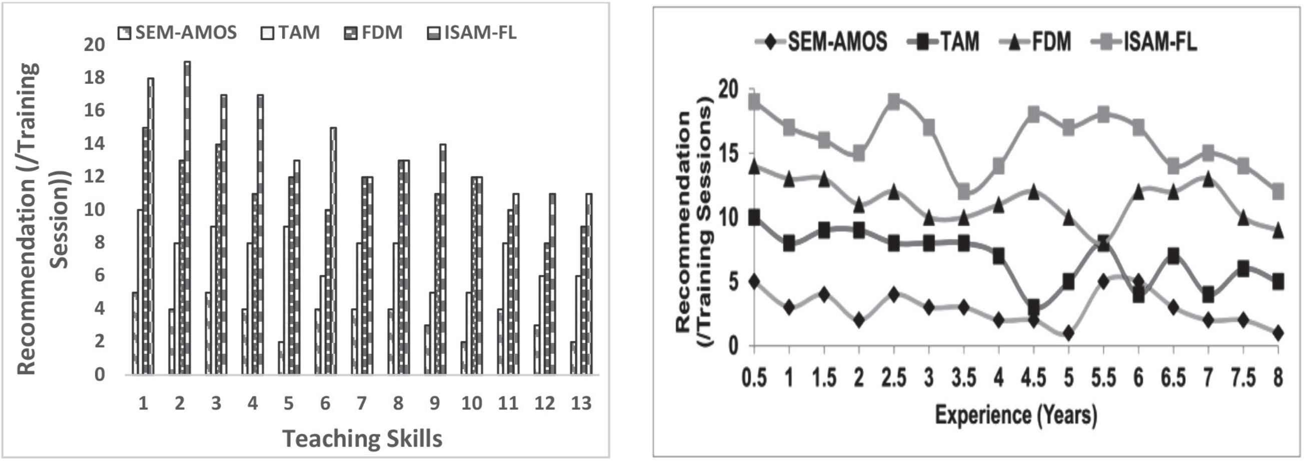
(a) (b)

Figure 9 Skill improvement.

of trainees in specific areas. With fuzzification, the vocational training process becomes more personalized and adaptive. Trainers identify the strengths and weaknesses of each individual and tailor the training content accordingly. This approach enables targeted skill development, allowing students to focus on areas where improvement is most needed. Furthermore, fuzzification levels enable trainers to track the progression of skills over time. By periodically assessing trainees' performance and adjusting the fuzzification levels, trainers can provide ongoing recommendations for continuous improvement. Overall, incorporating fuzzification levels in vocational training ensures personalized, targeted, and adaptive training experiences, and enhances the effectiveness of skills development (see Figure 9).

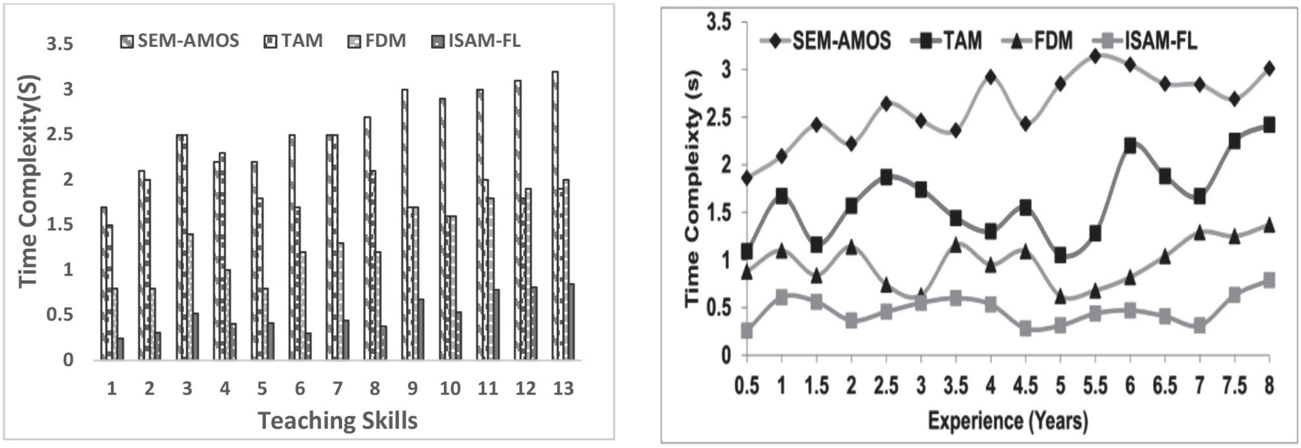
With this method, recommendation efficiency is improved because unnecessary or invalid assessments are excluded from the output. Highly effective recommendations are crucial in enhancing upcoming training sessions in vocational education. These recommendations are derived from various sources, including null and avoided assessments after fuzzification. By analyzing past sessions' successes and challenges, trainers identify improvement areas and incorporate relevant changes to optimize future training. By implementing these high recommendations, vocational education continually evolves and provides students with a dynamic and impactful learning experience. Efficient recommendations in vocational training sessions are generated by considering nullified and avoided assessments. By incorporating nullified and avoided assessments, trainers streamline the training session, optimize resources, and ensure that assessments are meaningful, relevant, and aligned with the desired learning outcomes. This leads to more efficient and effective recommendations for improvements in vocational training (Figure 10).

The complexity of the time is less in this process with the precise production of effective recommendations for the upcoming training sessions. Implementing fuzzification levels in vocational education training contributes to lesser time complexity. Fuzzification involves converting qualitative data, such as skill levels, into quantitative values. By assigning fuzzy membership functions and utilizing algorithms, the categorization and assessment of trainees' skill levels are automated and streamlined. This automation reduces the time and effort required for manual evaluation, enabling trainers to analyze and process large amounts of data efficiently. By leveraging less time complexity through fuzzification levels, trainers can allocate more time to delivering personalized instruction, providing targeted feedback, and designing effective training interventions. This ultimately enhances the overall efficiency and effectiveness of vocational education training (Figure 11).



(a) (b)

Figure 10 Recommendations.

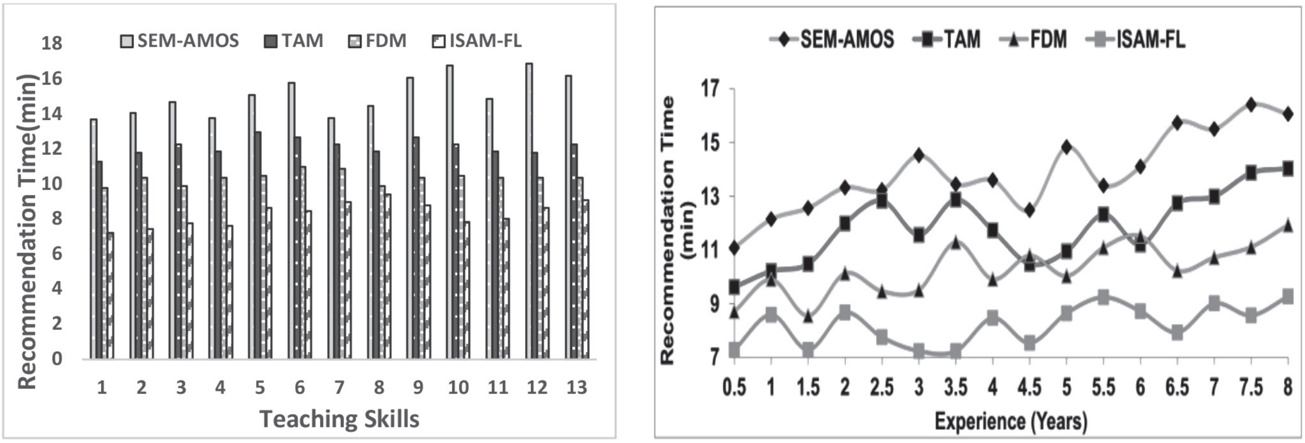


(a) (b)

Figure 11 Time complexity.

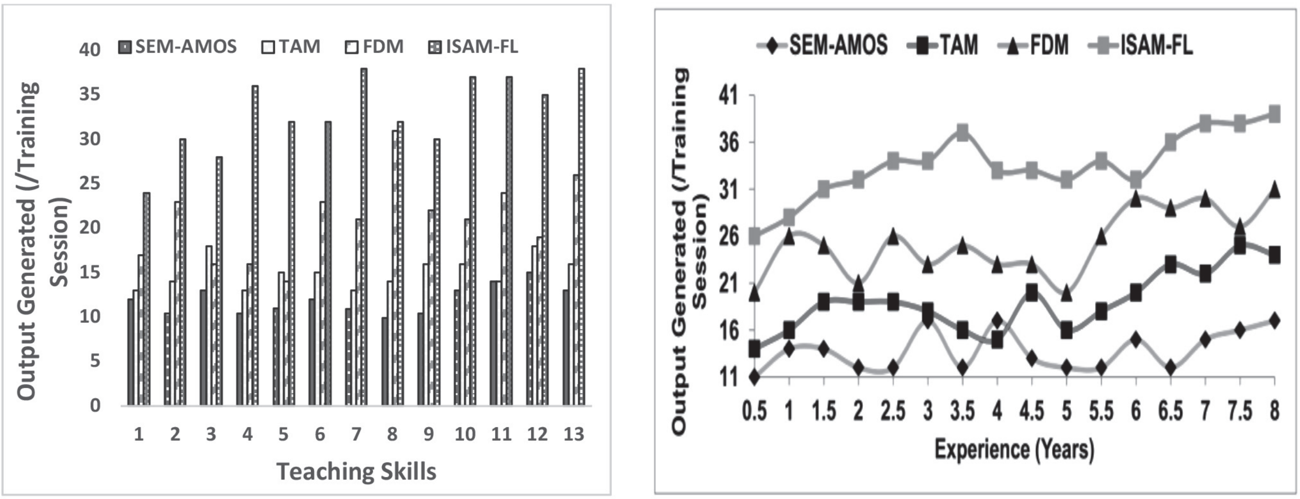
The efficient production of recommendations for enhancing upcoming vocational training sessions can significantly reduce the time required. This is achieved through various strategies. Firstly, leveraging the analysis of past session feedback, performance data, and industry trends provides valuable insights for generating recommendation. Additionally, establishing clear assessment criteria and streamlined evaluation processes saves time assessing trainee progress. By minimizing the time spent on producing recommendations, vocational training sessions benefit from more focused planning, prompt implementation of improvements, and ultimately create a more productive and time-effective learning environment. The implementation of efficient processes and the leveraging of fuzzification approaches in vocational education training significantly reduce the time required to generate recommendations. Trainers expedite the recommendation process by streamlining assessment methods, utilizing automation tools, and leveraging advanced analytics, facilitating the prompt implementation of improvements and timely feedback to enhance the training experience (Figure 12).

The established outputs are efficacious in this method due to using the fuzzification process to extract the nullified and avoided assessment results. The utilization of fuzzification levels in vocational education training generates valuable outputs that greatly enhance the learning experience. Trainers obtain precise and personalized assessments of trainees' capabilities by applying fuzzy membership functions to quantify skill levels. This enables the creation of tailored learning paths, targeted interventions, and customized feedback, resulting in more effective skills development. Fuzzification levels also facilitate the identification of specific areas for improvement and allow trainers to track progress over time. This fuzzification approach enables decision-making, ensuring that resources and instructional strategies are optimized to meet individual needs. Ultimately, using fuzzification levels in vocational education training led to improved learning outcomes, increased learner engagement, and enhanced the overall effectiveness of the training process (Figure 13). Further, the recommendation accuracy is evaluated; the obtained results are illustrated in Figure 14. In



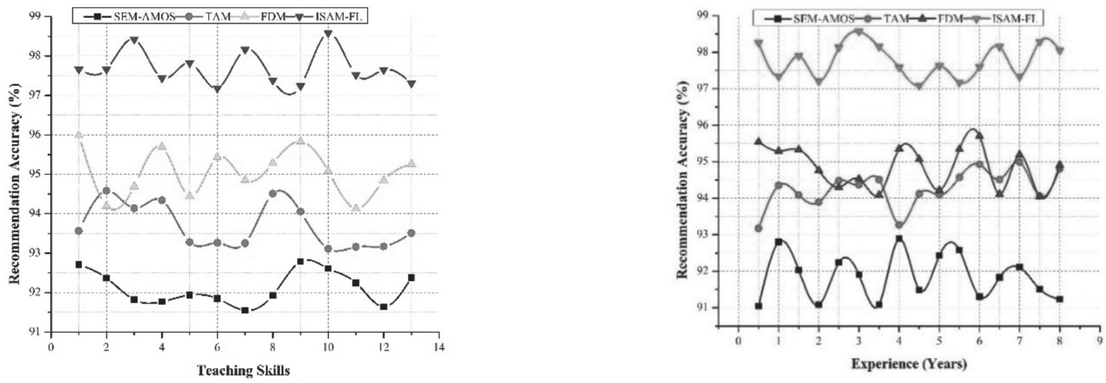
(a) (b)

Figure 12 Recommendation time.



(a) (b)

Figure 13 Outputs generated.



(a) (b)

Figure 14 Recommendation accuracy.

Table 2 Efficiency analysis.

Metrics	SEM-AMOS	TAM	FDM	ISAM-FL
Instructor effectiveness	High	Medium	Medium	High
Learning Outcome	High	Medium	Medium	High
Retention Rate	Medium	Medium	Low	High

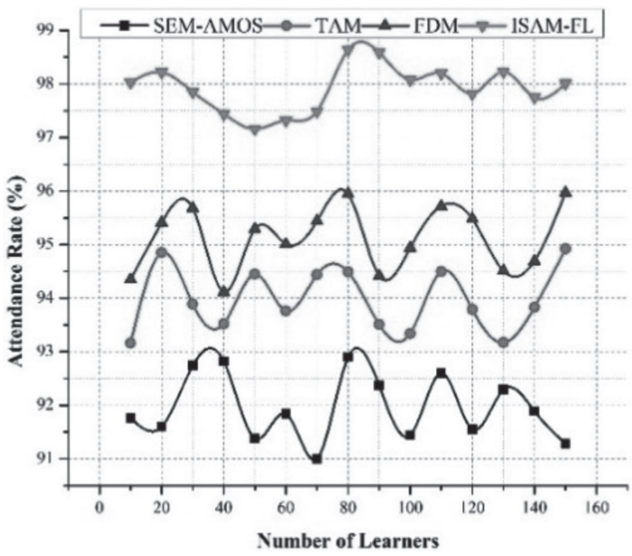


Figure 15 Attendance rate.

addition, the instructor effectiveness, learning outcomes and retention rate is evaluated; the obtained results are presented in Table 2.

Figure 14 shows that the proposed approach recommends the best education and teaching environment with maximum accuracy for various teaching skills (98.03%) and years of experiences (98.103%). The method uses the fuzzy approach and learning skills which maximize the overall learning efficiency compared to other methods. As seen in Table 1, the proposed ISAM-FL approach utilizes the fuzzy logic that ensures the effective evaluation and instructor effectiveness in different teaching environments and with different teaching styles. In addition, the learning process can adapt to a dynamic environment and consider the feedback, which improves the learning outcomes more so than other methods. Hence, the ISAM-FL approach is more responsible and adaptable, which makes it more effective than other methods in maximizing the retention rate.

Further, the efficiency of the system is examined using a learner engagement metric which helps to understand the learners' level of active participation and involvement in the educational process. The learner engagement level correlated with the information retention and high-level satisfaction in the learning process. The efficiency of learner participation is explored using attendance rate and assignment completion rate. The obtained results are illustrated in Figure 15.

Figure 15 shows the attendance rate of students, which helps to understand how actively the learners participate in the learning process. During the analysis, the frequent observations of 150 learners showed that the proposed system ensures 97.99% of attendance rate, indicating better performance compared to the other methods. However, even though students may attend classes regularly, their assignments should be completed and submitted on time. The assignment completion rate is illustrated in Figure 16.

Figure 16 demonstrates that the introduced method attains the high assignment completion rate compared to other approaches because it provides a more effective learning process and environment.

4. CONCLUSION

In summary, the Instructor Skill-based Assessment Method (ISAM) using fuzzy logic (FL) is a valuable addition to the field of VE. By analyzing VE performance through the lens of instructor skills, this method offers a comprehensive approach to improving the digital economy. Utilizing different fuzzification levels prevents nullified assessments, preserving valuable insights for performance evaluation. Additionally, the recommendation mechanism based on avoided nullified assessments enables instructors to continuously update their knowledge and enhance their skills, contributing to both their professional growth and the advancement of the digital economy. In conclusion, the proposed ISAM using FL is a dual improvement approach that benefits instructors and the digital economy. By leveraging instructor-centric education, VE responds more effectively to the challenges and opportunities of the digital economy. The ISAM provides a robust framework for evaluating VE performance and guiding instructors' professional development. Ultimately, this contributes to the overall enhancement of VE and its positive impact on the digital economy. The comparative study shows that the proposed method improves 8.38%

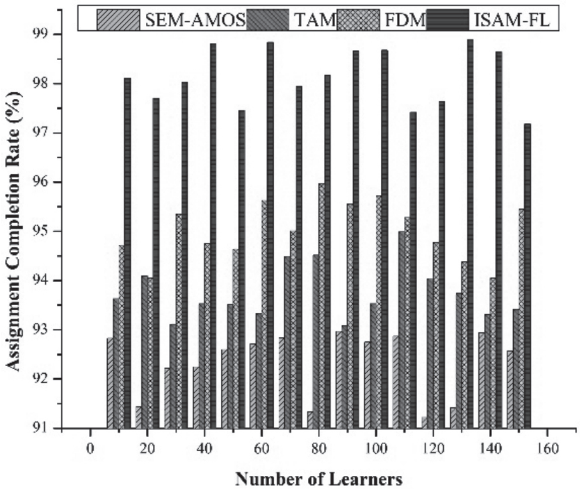


Figure 16 Assignment completion rate.

of recommendations and reduces recommendation time by 11.31% for the different skillsets. In addition, the method ensures the high effectiveness of instructors, and better retention rate and learning outcomes compared to other methods.

REFERENCES

1. Billert, M. S., Weinert, T., de Gafenco, M. T., Janson, A., Klusmeyer, J. & Leimeister, J. M. "Vocational training with microlearning - how low-immersive 360-degree learning environments support work-process-integrated learning", *IEEE Transactions on Learning Technologies*, vol. 15, no. 5, pp. 540–553, 2022.
2. Chiang, F. K., Shang, X. & Qiao, L. "Augmented reality in vocational training: A systematic review of research and applications", *Computers in Human Behavior*, vol. 129, pp. 107125, 2022.
3. Jin, X., Tigelaar, D., van der Want, A. & Admiraal, W. "Novice teachers' appraisal of expert feedback in a teacher professional development programme in Chinese vocational education", *Teaching and Teacher Education*, vol. 112, pp. 103652, 2022.
4. Seizinger, M. & Brunner, J. O. "Optimized planning of nursing curricula in dual vocational schools focusing on the German health care system", *European Journal of Operational Research*, vol. 304, no. 3, pp. 1223–1241, 2023.
5. Vandenberg, P. & Laranjo, J. "Vocational training and labor market outcomes in the Philippines", *International Journal of Educational Development*, vol. 87, pp. 102501, 2021.
6. Skovhus, R. B. & Poulsen, B. K. "A broader educational and vocational outlook in compulsory education has consequences for social justice", *International Journal for Educational and Vocational Guidance*, vol. 21, no. 1, pp. 1–16, 2021.
7. Dahalan, F., Alias, N. & Shaharom, M. S. N. "Gamification and game-based learning for vocational education and training: A systematic literature review". *Education and Information Technologies*, pp. 1–39, 2023.
8. Ordemann, J. "Higher education graduates, vocational qualification, and income. Is higher education worthwhile for dual qualifiers?" *Zeitschrift für Erziehungswissenschaft*, vol. 26, no. 3, pp. 1–27, 2023.
9. Hellne-Halvorsen, E. B., Lahn, L. C. & Nore, H. "Writing competences in Norwegian vocational education and training: How students and apprentices express their professional competences", *Vocations and Learning*, vol. 14, pp. 243–264, 2021.
10. Findeisen, S., Jüttler, A., Neuenschwander, M. P. & Schumann, S. "Transition from school to work–Explaining persistence intention in vocational education and training in Switzerland", *Vocations and Learning*, vol. 15, no. 1, pp. 129–154, 2022.
11. Getz, L., Langenkamp, K., Rödel, B., Taufenbach, K. & Weiland, M. "Open access in vocational education and training research: results from four structured group discussions", *Empirical Research in Vocational Education and Training*, vol. 12, no. 1, pp. 1–24, 2020.
12. Findeisen, S. & Wild, S. "General digital competences of beginning trainees in commercial vocational education and training", *Empirical Research in Vocational Education and Training*, 14, no. 1, pp. 2, 2022.
13. Zhou, N., Tigelaar, D. E. & Admiraal, W. "Vocational teachers' professional learning: A systematic literature review of the past decade", *Teaching and Teacher Education*, vol. 119, pp. 103856, 2022.
14. Choi, S. "The impact of education levels and paths on labor market outcomes in South Korea: Focusing on vocational high school graduates", *Social Sciences & Humanities Open*, vol. 4, no. 1, pp. 100152, 2021.
15. Wang, Y. L., & Chiang, T. Y. "Further study for the ordered weighted averaging operator",*IAENG International Journal of Applied Mathematics*, vol. 53, no. 3, pp. 39–46, 2023.
16. Shi, F. R., Zhao, N. N., Ouyang, X., Xu, H. B., & Zhou, Y. Q. "Adaptive fuzzy funnel control for pure-feedback nonlinear system with input constraint",*IAENG International Journal of Computer Science*, vol. 48, no. 2, pp. 334–342, 2021.
17. Abdullah, S. A., Saud, M. S., Hisham, M. H. M., Abd Wahid, N. H., Arsat, M., Suhairom, N. & Aripin, M. A. "Determining elements in mobile learning implementation among instructors in vocational colleges: A fuzzy Delphi method", *IEEE Access*, vol. 9, pp. 150839–150845, 2021.
18. Delcker, J. "Digitalization in the curricula of vocational schools: text mining as an instrument of curricula analysis", *Technology, Knowledge and Learning*, vol. 28, pp. 999–1014, 2022.
19. Chukwuedo, S. O. & Ohanu, I. B. "Optimizing vocational identity status and job search behavior via career-related practical skills training in electrical/electronic technology education", *International Journal for Educational and Vocational Guidance*, pp. 1–28, 2022.
20. Chukwuedo, S. O., Onwusuru, I. M. & Agbo, N. M. "Practitioners' vocational guidance with direct learning model: Influencing

career commitment and employability in electrical/electronic technology education", *International Journal for Educational and Vocational Guidance*, pp. 1–26, 2021.

21. Huang, Y. & Liu, X. "The analysis and research of STEAM education based on the TAM algorithm model to improve the learning effectiveness of higher vocational engineering students", *Evolutionary Intelligence*, vol. 15, no. 4, pp. 2597–2607, 2022.
22. Calero López, I. & Rodríguez-López, B. "The relevance of transversal competences in vocational education and training: a bibliometric analysis", *Empirical Research in Vocational Education and Training*, vol. 12, pp. 1–19, 2020.
23. Dogara, G., Saud, M. S. B. & Kamin, Y. B. "Work-based learning conceptual framework for effective incorporation of soft skills among students of vocational and technical institutions", *IEEE Access*, vol. 8, pp. 211642–211652, 2020.
24. Conejero, J. M., Preciado, J. C., Prieto, A. E., Bas, M. C. & Bolós, V. J. "Applying data driven decision making to rank vocational and educational training programs with TOPSIS", *Decision Support Systems*, vol. 142, pp. 113470, 2021.
25. Zwart, D. P., Noroozi, O., Van Luit, J. E., Goei, S. L. & Nieuwenhuis, A. "Effects of digital learning materials on nursing students' mathematics learning, self-efficacy, and task value in vocational education", *Nurse Education in Practice*, vol. 44, pp. 102755, 2020.
26. Romero-Gázquez, J. L., Cañavate-Cruzado, G. & Bueno-Delgado, M. V. "IN4WOOD: A Successful European Training Action of Industry 4.0 for Academia and Business", *IEEE Transactions on Education*, vol. 65, no. 2, pp. 200–209, 2021.
27. Pei, Y. & Lu, G. "Design of an intelligent educational evaluation system using deep learning", *IEEE Access*, vol. 11, pp. 29790–29799, 2023.
28. Chukwuedo, S. O., Mbagwu, F. O. & Ogbuanya, T. C. "Motivating academic engagement and lifelong learning among vocational and adult education students via self-direction in learning", *Learning and Motivation*, vol. 74, pp. 101729, 2021.
29. Wu, Y. "Innovation path of secretarial education in higher vocational schools based on internet environment and machine learning", *Soft Computing*, pp. 1–11, 2023.