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Enhancing intercultural competence in technical higher education through AI-driven frameworks

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The assessment of Intercultural Competence (IC) is increasingly recognized as an essential component of students' professional competency development in higher education settings. This study looks at the objectives of creating ICC and offers an assessment framework that adheres to the competency cultivation principles and the IC acquisition model. However, because intercultural communicative competence is not given enough attention, there are still problems with teaching abroad. This study utilizes the AI approaches for assessing the ICC in higher education. The Apriori algorithm analyses the association among the instructional tasks and ICC learning outcomes to find the teaching strategies most effectively build the cultural knowledge. Fuzzy logic is utilized to convert the qualitative perceptions to quantifiable data to address the subjective assessment, Sim Rank evaluate the student performance similarity and behavior to find the clusters and MK means used to segment the students based on ICC profiles for targeted interventions. The concepts and methods of model construction were applied in the development of a fuzzy thorough assessment model for college students' ICC. The findings show a substantial relationship between the total IC level and the four IC components of attitude, knowledge, Skill and consciousness. According to correlation strength, these characteristics are rated as follows: attitude (0.835), skill A (0.885), Skill B (0.823), Consciousness (0.714) and knowledge (0.972). Furthermore, there is a positive association between cross-cultural factors and the five aspects of English language ability, indicating a reciprocal relationship between developing IC and learning English.

Keywords Interculture competence, Artificial intelligence, Fuzzy, Higher education, Clustering

The importance of inter-cultural communication skills have grown significantly in today's society. More and more people in our civilization are interconnecting due to the advancement of technology and Artificial Intelligence (AI)[1]. Communities need individuals who canembrace, handle, and adapt to different cultures. Such changes are already being experienced in in the classroom where students come from different localities or countries. Culture being dealt with the manner of approach to an individual from a culture different from the one taught from. In communication, understanding and related activities and dimension language of some distinct ends. It involves speaking the language of the person one is dealing with and size the way incorporate differences one you communicate.

Due to globalization, interactions with individuals from different cultures have become more common, underscoring the need for these skills. Thus, it is important for learners to develop the knowledge and skills necessary to interact with individuals from different cultural frameworks. Knowledge concepts, emotional attunement to cultural differences, and action in the context of the world, implement and use a cultural communication model in practice, are all essential for building cultural communication competency. In education, sociology, and communication studies, ICC has been researched profoundly. Models that combine language ability with cultural knowledge and attitudes have been put forth by academics like Byram (2021)[2], who contend that true competence results from the interaction of these elements. These models highlight that ICC is a transforming process where people become conscious of their own cultural prejudices and learn how to interact with others in a courteous and productive manner. It is not only about learning facts about other cultures.

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By overcoming linguistic and cultural barriers, the introduction of AI has brought about revolutionary technologies that greatly improve this kind of communication[3]. The way people from diverse cultural backgrounds interact has been completely transformed by AI tools, especially those made for language acquisition and translation[4]. The special requirements of students from various cultural backgrounds are frequently ignored by traditional language learning frameworks. Nevertheless, AI-powered solutions that address these diverse needs, like the Cross-Cultural Intelligent Language Learning System (CILS), provide tailored, adaptable learning experiences. By dynamically modifying content and teaching strategies with the use of cutting-edge AI technology, CILS greatly enhances students' language skills and cultural awareness[5,6].

While educational applications of AI are not new, they have certainly expanded in recent years. AI has the power to transform education in many critical areas such as assessment, personalized instruction, and the development of soft skills including culture and communication[7]. Furthermore, AI has become a vital tool for language acquisition due to its capacity to evaluate massive datasets and offer real-time feedback. It is used by programs like Rosetta stone and Duolingo to modify courses according to user performance, providing more engaging and individualized learning experiences. This can assist users comprehend the cultural settings in which the language is used by emphasizing language skills and including cultural material[8,9].

ChatGPT and other tools have been incorporated into educational platforms to support cultural competency-focused telecollaboration assignments. These resources improve students' ICC by empowering them to communicate in a way that is appropriate for their culture. Students can investigate various cultural situations and get a stronger comprehension of cultural nuances by imitating AI-generated assignments[10]. Language translation is one of the most straightforward and useful uses of it in cross-cultural communication (CCC). AI assisted translation tools, like DeepL, Google Translate, and other language models, offer precise translations in real time, facilitating communication between speakers of different languages. These resources are essential for removing linguistic barriers and facilitating international communication and cooperation[11]. Furthermore, these translation systems are always getting better thanks to AI's capacity to pick up on and adjust to various linguistic patterns and cultural situations. For effective CCC, this flexibility guarantees that translations are both linguistically correct and culturally relevant[12].

There are difficulties and debates associated with integrating AI into education, especially in ICC. The potential of this technology to improve and challenge conventional teaching methods is a common current discussionof education today. Furthermore, it can greatly improve the learning process by personalizing instruction, automating repetitive chores, and providing real-time feedback. However, there are also worries about the ethical ramifications of AI, namely with regard to data privacy, the perpetuation of cultural prejudices, and the possibility that would de-humanize education by decreasing in-person encounters. The possibility that will perpetuate cultural biases is one of the most important ethical issues. AI systems are trained on large datasets that might contain deep biases reflecting societal prejudices. If these prejudices are not addressed, these systems may serve to strengthen stereotypes rather than advance cultural awareness. In intercultural communication, in which the goal is to promote empathy and respect.

For difference, this is particularly alarming. Ensuring these emerged technologies are designed and deployed to facilitate diversity and cultural sensitivity is key to reducing this risk. This involves ongoing auditing of this systems to locate and correct any possible bias as well as training AI algorithms on multiple relevant datasets. According to Hashemian and Farhang-Ju[13], L2 theory and research have incorporated ICC. Introversion, extraversion, intuition, sensation, and judgment are all stronger among the participants. In 2020, Bagui and Adder[14] concentrated on the comprehensive investigation. The majority of students exhibit unfavorable attitudes, indicating that they lack the cultural competency necessary to prevent cross-cultural disputes in a variety of literary lectures. Idris (2021)[15] suggested certain ICC based competences for EFL in order to have a thorough understanding of ICC. Language, sociolinguistics, discourse, IC, and intercultural awareness are among the competencies that might aid EFL in Indonesia to enhancing both their own and their students ICC[16].Due to a lack of systematic and thorough review and a dearth of quantitative empirical studies, current research is somewhat dispersed. Thus, the work employs a systematic comprehensive assessment of higher education students' ICC as well as the fuzzy comprehensive evaluation approach. Fuzzy mathematics serves as the foundation for the fuzzy comprehensive evaluation approach. The novelty and the contribution of this paper is as follows:

- This study analyzes the objectives of ICC in the context of AI and discusses the competence performance with evaluation. The Apriori method is used to examine the connections between instructional tasks and ICC development to create a weight matrix the factorsto clarify the connection between the two. We selected this approach based on its potential to reveal associative relationships between instructional activities and ICC growth. The educational justification stems from the curriculum being informed through the identification of formative learning processes, as explained in "Weighting Matrix Computation for Teaching Activities".
- The similarities among the students are determined using modified SIM approach and the students are grouped into discrete groups using the Modified K-means algorithm. SimRank similarity measure makes more sense in modeling students who share cross cultural experiences or have shared learning journeys with other students. Unlike and more traditional measures such as cosine similarity, SimRank adopts the approach that "two nodes are similar if they are related to similar nodes," which is appropriate for the networked view of modeling peer exposure to and culture and learning patterns (see Section III). This applies for student grouping. We demonstrate how cross-section ICC development patterns for various demographic and behavioral cohorts are actionable for educators in terms of intervention design (see Section IV, "Student Grouping").
- The novelty of this paper is the incorporation of the fuzzy concept to evaluate the ICC Of the higher education students. The concepts and methods of model construction were applied in the development of a fuzzy thorough assessment model for college students' ICC. This comprehensive fuzzy evaluation can change the qualitative evaluation into quantitative based on the degree of membership. Its use is justified in ICC assessment

because of its fundamentally subjective and multidimensional character. ICC includes attitudes, knowledge, skills, and consciousness—elements which are not clearly defined. Fuzzy logic provides a sophisticated, quantitative measurement of such qualitative attributes which can be, for example, termed as assessed rather than purely compared in a comparative analysis (refer to Section IV, "ICC Evaluation Using Fuzzy").

- Evaluation scales and a set of dimensions were developed. Cross-cultural skills are used to assess the questionnaire's indices, selection, and weight connection. According to correla on strength, these characteristics are rated as follows: attitude (0.835), skill A (0.885), Skill B (0.823), Consciousness (0.714) and knowledge (0.972). Furthermore, there is a positive association between cross-cultural factors and the five aspects of learning ability, indicating ti a reciprocal relationship between developing ICC and learning.

The structure of this paper is ordered as follows: Section II discusses the literatures related to ICC and AI for students. Section III describes the AI based methodologies that assist ICC and proposed methods for ICC evaluation of higher education students. Section IV discusses the experimented results qualitatively and compared. Section V concludes the paper with the advantages and future enhancement.

Literature review

Zhong and Doumei, (2024)[17] examines the goals of ICC cultivation and suggests an evaluation plan that is in line with the ICC acquisition model and competency cultivation principles. To shed light on the relationship between teaching activities and ICC development, the Apriori method is utilized to analyze the relationships between the two and build a weight matrix for each activity. Additionally, students are clustered into distinct groups using the K-means approach, and similarities between students are found using the Sim Rank algorithm. By examining the differences in assessment results, the viability of the assessment method is confirmed. Along with analyzing students' perspectives toward ICC graphically, this study looks at how the five components of English proficiency speaking, writing, reading and translating affect ICC. By contrasting and choosing thorough evaluation techniques, Long and Lin, (2022)[18] provided a theoretical explanation of the current cross cultural competence dimensions and assessment scales using factor analysis. Its primary benefits were straightforward mathematical models and simple operation. The morality and concepts of model creation, the procedures and phases of model construction, and model computations were all included in the development of an extensive assessment method for higher education students' cross-cultural competency. The survey's findings demonstrated a strong positive relationship between the samples' four level scores and their CCC abilities, attitudes, and foreign cultural awareness.

The usefulness of incorporating AI technology to improve the motivation, engagement, and attitude of EFL learners while lowering their learning anxiety is examined by AlTwijri and Alghizzin(2024)[19], . By looking at titles and abstracts, publications from reliable journal databases which were filtered out of the search. Only 21 of the 64 publications that were examined and published between 2017 and 2023 were found to be pertinent to the subject of the study. The results indicate that the use of this technology in EFL situations is still in its infancy, and more study is needed to determine how AI-integrated lessons affect the affective variables of EFL learners.

Klimovaand chen (2024)[20] evaluates the effects of AI-driven tools, includes chatbots and virtual reality simulations, on students' capacity to deal with cultural differences by combining the results of 11 empirical investigations carried out worldwide. Even while AI can greatly enhance learning personalization and create immersive cultural experiences, there are still obstacles to overcome, especially when it comes to guaranteeing cultural sensitivity and resolving disparities in access to technology. In order to minimize biases and improve cultural awareness, the review warns the audience concerning potential hazards and emphasizes the necessity of human oversight when integrating AI in education. The educational implications emphasize how crucial it is to combine this with conventional teaching techniques in order to establish inclusive learning environment that equip students for the needs of a worldwide society. Qiaoqiao and Juncheng, (2024)[21] examines the current state of intercultural communication studies, identifies issues with the current research, and attempts to propose intercultural communication cultivation techniques by reviewing and summarizing earlier studies on the subject.

Chen et al., 2024[22] research demonstrates how learners may adjust to various cultures with AI-based language translators & cultural simulators. Constructivism holds that learning happens when students actively build their knowledge from experiences in order to become more culturally sensitive, comprehend, and respect different cultures while also lessening stereotypes. According to CHAT, AI is one of the tools or artifacts available to humans to promote social connection; as such, it has the potential to improve CCC in situations where non-verbal cues are just as important as language ones. Surveys were used to reach 228 respondents in total, and early findings indicate that accommodating technologies like language translators using AI models or software simulations tailored to a particular culture have improved CCC.

In their discussion of the function of visual media in language learning, Crowther et al., (2017)[23] came to the conclusion that it is an excellent and highly suitable learning tool that is particularly important for fostering students' ICC and cultural awareness. Suzuki et al., (2021)[24] investigated how study abroad programs affected the intercultural communicative competence of aspiring English language teachers and came to the conclusion that pre-service teachers' sophisticated grasp of the language caused them to rethink how they use it, confirming that the growth of ICC can support language learning. Lee J (2020)[25], combined Korean and American students learning English into a single group and conducted a small group intercultural communication exercise. The results showed that while the frequency and density of communicative messages did not significantly differ among the two groups of students, the quality of the improved interactions, and this type of communication promoted the development of cultural communication skills while facilitating the formation of transnational friendships.

Methods and materials

This section discusses the methodologies used for assessing the ICC in higher education like colleges for both theory and practice.

AI in teaching

There is an unavoidable growing tendency for big data and intelligence in traditional fields. Artificial intelligence in conventional domains is very compatible with the features of the education sector. Consequently, a popular topic in artificial intelligence applications is the integration of AI with the educational sector. Currently, China is steadily developing certain related software and network resources for college students to learn artificial intelligence courses. However, the effectiveness of websites is diminished by their poor rate of information updates. As a result, website upkeep should be given greater significance in order to provide it authentic viewpoints and make it better suited for virtual teaching. Search engines, online libraries, literature repositories, blogs, and Wikipedia are just a few of the many learning resources available on the Internet for individual study or online exploration instruction. Because so few people are now studying AI education, there aren't several blog assets for teaching logs and reflections. Researchers must create such resources since network platforms are not been the most successful in education exchanges. Figure 1 illustrates the teaching and learning through AI. A number of fundamental issues in education, including instructing pupils according to their potential, unequal resource distribution, a lack of training in innovative skills, and other issues, can be resolved by artificial intelligence.

Proposed methodologies ICC of higher education

Figure 2 depicts the theory-and practice-based approach of ICC acquisition for college students. The three components of ICC intercultural awareness, attitude, knowledge, and skills form the basis of the paradigm. Six links are created in order to gradually accomplish these three components. These links include professional instruction, interest-based learning, individual study, communicative engagement, foreign language instruction, and real-world experience.

Ethical considerations

This study was conducted in accordance with ethical research guidelines and was approved by the Department of Educational Foundations and Humanities, Faculty of Education, Universiti Malaya, Kuala Lumpur, Malaysia. All participants provided informed consent before completing the questionnaire. Participation was voluntary, and respondents were informed that they could withdraw at any time without consequences. To ensure confidentiality and anonymity, all collected data were anonymised and securely stored, accessible only to the research team. Figure 3 illustrates the conceptual diagram of choosing the methods. The Apriori algorithm is anlayzes the association among the instructional tasks and ICC learning outcomes to find the teaching strategies most effectively build the cultural knowledge. Fuzzy logic is utilized to convert the qualitative perceptions to quantifiable data to address the subjective assessment, SimRank evaluate the student performance similarity and behavior to find the clusters and MKmeans used to segment the students based on ICC profiles for targeted interventions.

Dimensions of ICC

This study utilizes the Fantini's ICC dimension methods. Table 1 illustrates the ICC assenting factors for evaluating the ICC scale of the high education students.

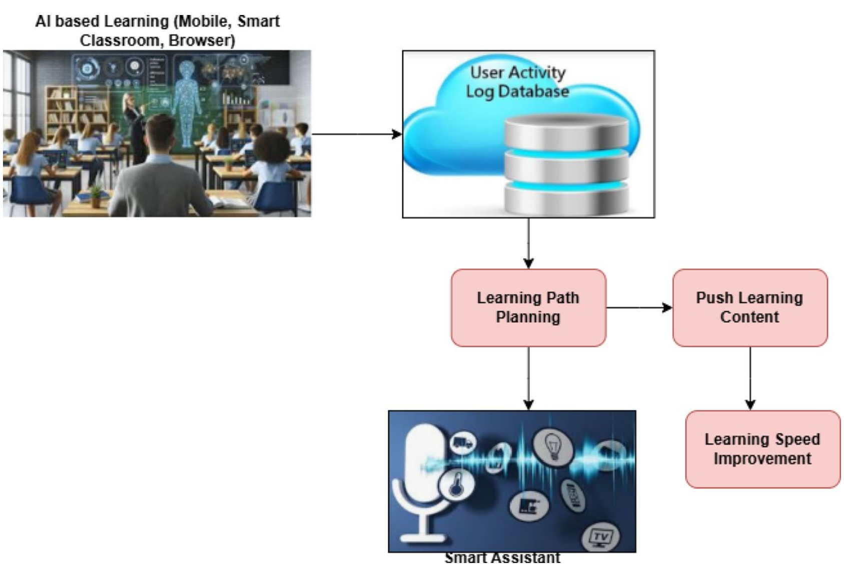

Fig. 1. AI assisted framework for learning and teaching.

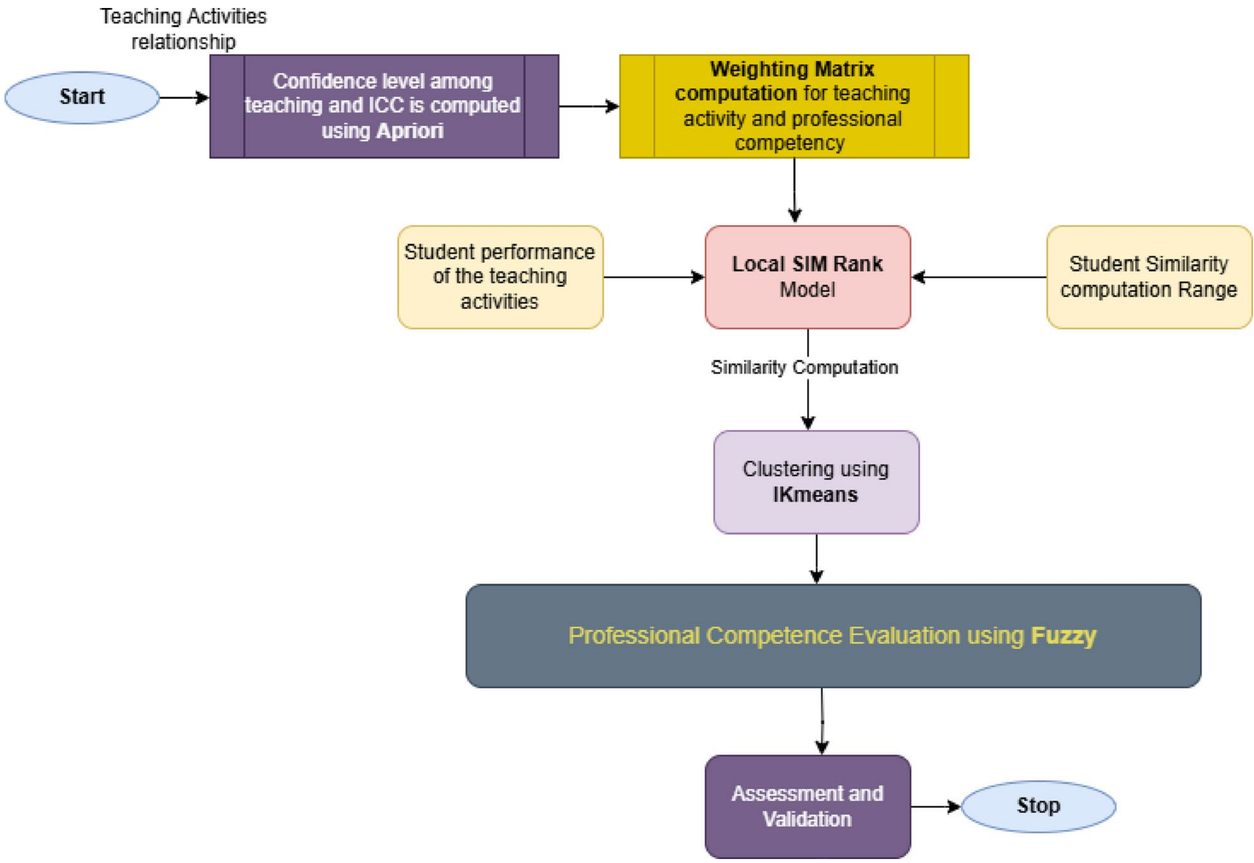

Fig. 2. Assessment scheme using AI framework for ICC.

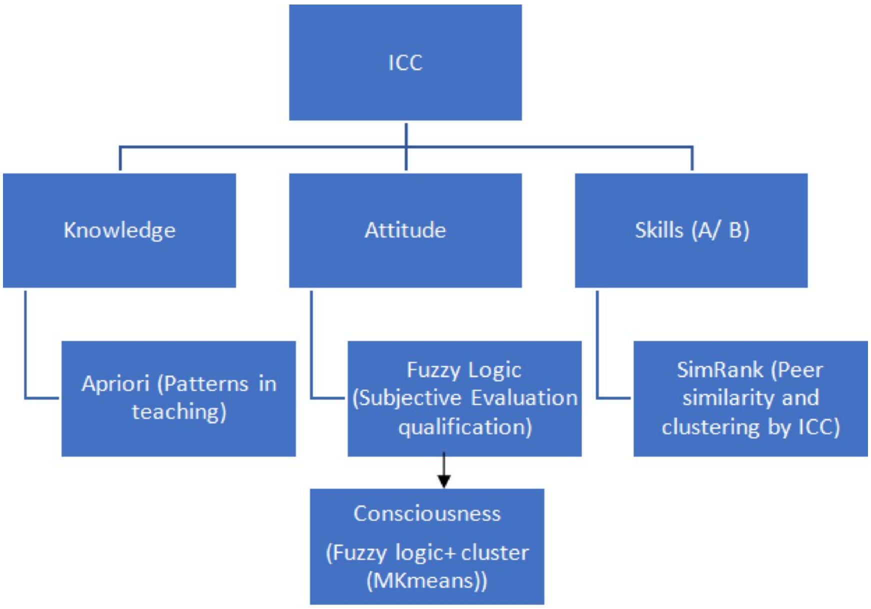

Fig. 3. Conceptual diagram of Mapping AI tools onto ICC.

Weighting matrix computation for the teaching activities

Based on the connection among teaching actions and the student's development ICC, the Apriori method is used to analyze the degree of correlation where the confidence is 0.03 and support is 1. The Eq. (1) is utilized to compute the confidence level among the instructional activity $I_i$and competency of student C_i The weight

Index	Values
Index for Normal Adaptation (INA)	0.83
Index for Comparative Fit (ICF)	0.93
Index for Non-Standard Fit (INSF)	0.92
Index for Fitness (IF)	0.92
Index for Adjust Fitness (IAF)	0.94
Mean square and square root of residual error (MSRE)	0.06
Asymptotic residual mean square error (ARMSE)	0.02

Table 1. Considering factors for ICC.

among the teaching and student activity V_{I_i,C_i}. The W_{I_i,C_i} is computed so that the amount of weights of activity of teachers to support the students ability confidence is 1 and n denotes the number of teaching actions related to ICC development.

$$W_{I_i,C_i} = \frac{V_{I_i,C_i}}{\sum_{i=1}^{n} V_{I_i,C_i}} \tag{1}$$

Students' similarity computation using Local-SIM rank method

Sim Rank is a method that is used recursively to find the similarities among the two objects using the incoming neighbor similarity of the graph. It uses the tenet that "two objects are similar if they link to the similar objects" to determine how similar two objects are".For N nodes, Nodepairs similarity S is described as N*N, where the item S_{ij} is the nodepair score among the node i and node j.

Given a graph G(V, E) where V is the set of nodes and E is the set of links. N(v) is the all in neighbors of vth node. The notation |N(v)| declares the nodes count in N(v). The individual member of this N(v) denotes as, $N_i(v),\ 1 \le\ i \le\ |\mathrm{N}\,(\mathrm{v})|$.

With the SimRank score among object a to b is denoted as $S(a,b) \in$ [0,1], the recursive computation similarity is declared as,

$$S(v_a, v_b) = \begin{cases} 1 & (v_a = v_a) \\ \frac{c}{|N(v_a)||N(v_b)|} \sum_{i=1}^{|N(v_a)|} \sum_{i=1}^{|N(v_b)|} S(N_i(v_a), N_i(v_b)) & (v_a \neq\ v_a) \end{cases} \tag{1}$$

Where c is the constant among 0 and 1 as defined as decay factor. If $N(v_a)$ and $N(v_b)$ is an empty set and S(a, b) is specified as zero. At a certain point of iteration, the algorithm reaches the solution. For every iteration, the recursive similarity function S_{k+1} is defined. The links are defined using adjacency table. The recursive computation is started with s_0 as denoted as,

$$S_0(v_a, v_b) = \begin{cases} 0 & (v_a \neq\ v_a) \\ 1 & (v_a = v_a) \end{cases} \tag{2}$$

On the iteration of k+1, S_{k+1} is computed from S_k as follows:

$$S_{k+1}(v_a, v_b) = \frac{c}{|N(v_a)|\,|N(v_b)|} \sum_{i=1}^{|N(v_a)|} \sum_{i=1}^{|N(v_b)|} S_k(N_i(v_a), N_i(v_b)) \tag{3}$$

SimRank is known to have a long computation time and to calculate the similarity score of each pair of nodes after the SimRank calculation. In some cases, though, we only take into account the similarity scores of a limited number of node pairings. In that case, we waste a great deal of time on useless computations. This also know that links between websites are changing from time to time. After a short time, some links may be added to the internet, while others may not be reachable through the original resources. The establishment of the subgraph is the next step. Our main idea is to collect a small selection of nodes for LoaclSimRank and examine the local graph surrounding a node pair (a, b).

Student grouping using Modifed-Kmeans(MKmeans)

In this study, the distinct group of higher education students is clustered using modified K means based on grid density. We will compute the density of each point in order to identify the outliers; a point is considered an outlier when its density value surpasses a predetermined threshold. The compactness of a point often denotes the total amount of points in a circular region. In this manner, we must determine a point's distance from every other point in order to determine its density. The temporal complexity is $O(n^{2)}$ since we must determine the distances of every other point to a point in order to determine its density. In this, the outliers are detected using the grid density to reduce the time complexity. The algorithm counts the number of points within a certain range after sorting every point from a dimension. A threshold must first be established; a point is considered an outlier and eliminated if its density is less than this threshold.Selecting initial cluster centers comes after outliers have been eliminated. The initial cluster centers are created in order to achieve a better outcome, as the final cluster result is

Notations: SEED- set of nodes where each nodes denotes Seed node. TempX denotes the similarity result of temporary node set X, RandomWalk (X) denotes group of nodes either the neighbor node of every node in X.

Input: NodePair (a,b)

Output: Score for Similarity (SS) of node a and b

Phase: 1 – collection of SEED node set

$Seed \leftarrow \{a, b\}$

$TempA = \{a\}, TempB = \{b\}$

```
While(Random_Walk(Temp_A)∩Random_Walk(Temp_B)==∅)
 {
        Temp_A=Random_alk(Temp_A)
        Temp_B=Random_Walk(Temp_B)
}
Seed←Random_Walk(Temp_A)∩Random_Walk(Temp_B)
```

Phase 2: Extension

```
SS←SEED;
Temp_C←SEED
For (i=0;ii<m;i++)
{
Temp_C=Random_Walk(Temp_C);
SS←Temp_C;
}
```

Phase 3: Recursive Iteration

SimRank (SS)

Algorithm 1. LocalsimRank algorithm.

very sensitive to the original cluster centers. Initial cluster centers are generated at random by the conventional K-means technique. However, this random approach is inefficient and produces ambiguous results.

Two categories of cluster data exist: one is a distribution of data with clear segmentation and notable differences among each cluster, and distribution of data without clear segmentation. Initially, the ultimate clustering result is nearly the same regardless of the technique employed to create the initial centers. The approach taken is crucial in the second instance, though. Therefore, we create the initial cluster centers using a new, enhanced technique. For every dimension, we separate the data into K segments. In this dimension, the coordinate of the associated initial cluster center will be the each segment average value. The disparities between clusters may become more noticeable as a result of the great distance among each initial cluster center. Better clustering outcomes are produced by these initial centroids. The algorithm is described as follows:

Once, the student clusters are formed, it is analyzed as follows:

Input: Dataset D with n samples , m dimensions, cluster number k and the density threshold MinT

Output: Group of K clusters

Step 1: For each dimensions, compute the minimum and maximum values G_{min} and G_{max} where $(0 \leq G \leq m)$ and set the length of grid as,

$$L_G = \frac{(G_{max} - G_{min})}{k+1} \tag{4}$$

Step 2: For each student, compute the grid density.

Step 3: if (Value of grid density≤MinT) then remove it.

Step 4: Sort the values of each dimension G after the outlier removal. Divide it into k segments and compute the average value of each segment as $\{A_{g1}, A_{g2}, \dots A_{gk}\}$.

Step 5: The values from Step 4 are used as the coordinates of the initial cluster center k as, $\{C_1, C_2, \dots C_k\}, where\ C_k = \{A_{1k}, A_{2k}, \dots A_{mk}\}$.

Step 6: Compute the average similarity among the records using distance among new clusters to other records and assign it into the nearest cluster.

Step 7: For each cluster, the record with largest similarity is considered as center of cluster.

Step 8: Untill the cluster center does not change, repeat Step 6 and 7.

Algorithm 2. Modified K means with density threshold.

- Evaluation of students' total aptitude: compute each clustered student's professional performance using Eq. (5), then examine the beneficial professional skills that each clustered student possesses. Equation (5) is described as below:

$$S_{ap} = \sum\nolimits_{i=1}^{n} S_{k_i} * W_{k_i a_g} (1 \leq i \leq n) \tag{5}$$

Where, S_{ap} is the score of assessment and personnel ability, a_g is embodied by the students in the category g, S_{k_i} is the teaching activity average score of k clusters, $W_{k,a}$ is the teaching activity weight, k_i is the professional ability, n denotes the number of teaching activity.

- Analysis of variations in students' professional skills: various instructional exercises are selected as criteria to group students and contrast the variations displayed by student groups in various career paths.
- Assessment of students ICC using fuzzy which is described in following section.

ICC evaluation using fuzzy logic

To improve the comprehensive evaluation of the model, this study utilizes the fuzzy method for evaluating high education students ICC. A comprehensive evaluation technique founded on fuzzy mathematics is the fuzzy evaluation method. This comprehensive evaluation method, which applies fuzzy mathematics to arrive at a general evaluation of items or things that are bound by several parameters, transforms qualitative assessment into quantitative evaluation, according to the degree of membership theory of fuzzy mathematics. Its strong systematicity and unambiguous outcomes enable it to tackle a variety of non-deterministic problems as well as ambiguous and challenging-to-quantify issues.

The following are the general procedures for a fuzzy comprehensive assessment of higher education students' ICC. Establish the fuzzy evaluation conversion matrix of IC, the weight distribution among evaluation factors,

Mathematical expression	Values
$W = \{w_1, w_2, w_3, w_4, w_5, \}$(9)	(0.04,0.2,0.18,0.24,0.05,0.14)
$W_1 = (w_{11}, w_{12}, w_{13})$(10)	(0.32,0.26,0.3)
$W_2 = (w_{21}, w_{22}, w_{23}, w_{24}, w_{25}, w_{26}, w_{27})$(11)	(0.18,0.18,0.1,0.13,0.11,0.05,0.11)
$W_3 = (w_{31}, w_{32}, w_{33})$(12)	(0.4,0.16,0.32)
$W_4 = (w_{41}, w_{42}, w_{43}, w_{44}, w_{45}, w_{46}, w_{47}, w_{48}, w_{49})$ (13)	(0.08,0.17,0.14,0.11,0.15,0.05,0.11,0.12,0.04)
$W_5 = (w_{51}, w_{52}, w_{53})$(14)	(0.32,0.21,0.43)
$W_6 = (w_{61}, w_{62}, w_{63})$(15)	(0.34,0.41,0.33)

Table 2. Weight value of the indices.

Methods	What it is?	How it is used?	Why it is good for Eduction?
Apriori	Discovers common patterns and teaching activities tend to be most strongly linked to gains in students' intercultural competence	It reveals which students' ICC	Informs educators about which specific combinations of learning activities (e.g., projects, discussions) are best at promoting
SimRank	Calculate how similar two items (such as students) are based on their relations to other things that share similarities	It measures the intercultural traits of the students How the formation of valuable peer groups and focus on instruction where it's needed most	It groups students with similar intercultural profiles, which can allow peer interaction among the targeted institution
MK-means Clustering	Clustering data points together by similarity. What the basis of their ICC characteristics (i.e. attitude, knowledge, skill).	Students are divided into clusters on different groups of students, based on their level of intercultural competence	Teachers can tailor instruction to different groups based on their level of intercultural competence
Fuzzy Comprehe-nsive Evaluation (FCE)	Assesses qualitative factors using fuzzy logic, which deals with uncertainty and partial truths	Translates imprecise human judgments (e.g., "good," "average," "poor") regarding ICC into numerical values	Enables subjective qualities such as attitude and cultural awareness to be measured in a reproducible, computational manner

Table 3. Summarization of the utilized approaches.

the set of comments for the IC evaluation, and the set of factors for IC evaluation[26]. Next, create a fuzzy comprehensive assessment model in accordance with[27] for grade and grade two multifactors.

$$F = \{f_1, f_2, \ldots f_m\} \tag{6}$$

Where m denotes the number of evaluation and it is assumed as 5[28]

$$F = \{f_1, f_2, f_3, f_4, f_5\} \tag{7}$$

The factors F is defined as F = {Weaker/average/some, very$_{\text{weak}}$/slightly,Stronger/more, very_Strong/very_much}[29]

$$W = \{w_1, w_2, \ldots w_n\} \tag{8}$$

Where, W is the distribution of weight set. The data for evaluation have 20 domestic experts on various factors are gathered to evaluate the higher education students ICC and statistical processing. Based on Delphi method, the Table 2 shows the obtained weight indices[30]. For fuzzy computations, the weighted component sum must typically equal 1[31].

The association among the evaluation index with the rating has been established since each index's comment rating is determined by its judgment. The following is the ICC fuzzy evaluation transformation matrix R[32,33]:

$$T_{(j)} = [T_{1(j)}, T_{2(j)}, T_{3(j)},,,, T_{n(j)}] \tag{14}$$

$$T = \left[t_{m(j)}\right] = \begin{bmatrix} r_{11(j)} & r_{12(j)} & \cdots & r_{1n(j)} \\ r_{21(j)} & r_{22(j)} & \cdots & r_{2n(j)} \\ . & . & \cdots & \cdots \\ r_{m1(j)} & r_{m2(j)} & \cdots & r_{mn(j)} \end{bmatrix} \tag{15}$$

where, $t_{m(j)}$ is the fuzzy membership degree of T and the fuzzy model is denoted as follows

$$B = W \circ T = (w_1, w_2, w_3, w_4, w_5, w_6) \circ \begin{bmatrix} B_1 \\ \cdots \\ B_m \end{bmatrix} = (b_1, b_2, \ldots b_m) \tag{16}$$

where B is the fuzzy based ICC comprehensive evaluation result. Table 3 summarizes the used methodologies.

Results and discussions

Data collection model

Classroom lectures alone cannot complete the complex and time-consuming process of developing ICC. Teaching foreign languages is not the only method of acquiring ICC; literature, geography, and history can expose children to cultural understanding from a variety of viewpoints. In actuality, the development of ICC requires tight collaboration with other topics in addition to the support of society and the educational setting; it cannot be achieved alone through foreign language instruction. It is possible to cultivate ICC through teaching foreign languages, but in order to construct a full and successful model, it is imperative to develop many approaches.

The study circulated 1,300 questionnaires to the volunteers and the aggregated results are sued for this study, 325 for each grade, and collected 1,050 valid questionnaires, comprising 313 for freshmen, 295 for sophomores, 232 for younger students, and 210 for seniors. Additionally, 399 male students and 651 female students, or 62 and 38% of the gender ratio, correspondingly, answered the questionnaire survey. 27%, or 283 people, traveled overseas. 11%, or 112 immigrants from various cultures, had "a lot" of contacts. Among them 703 students (67%) are involved in ICC activities. The ICC scale consists of seven subclasses such as: ICC thorough assessment, knowledge of both domestic and international cultures, manner, Cross-cultural awareness and cognitive abilities, as well as intercultural communication capabilities.

The group deliberated, created an interview framework, and conducted interviews with each respondent to better understand the present state of students' intercultural communication competency in order to improve the research study's accuracy. The following are the interview questions based on Fantini (2009) scale:

1) In your opinion, what constitutes intercultural communicative competence?
2) Do you believe that your studies, social practice, and future employment will benefit from having strong intercultural communicative competence?
3) Do you believe that testing intercultural communicative competence is essential? Please provide justifications.
4) How can intercultural communication abilities be strengthened, in your opinion?

In order to assess the model, the parameters of the considered model are fixed as follows: the minimum confidence threshold is 0.03 that can filter out the weak associations among instructional task and ICC traits, number of cluster as 4 and 5 levels of fuzzy evaluation and the weighting matrix is based on apriori output. The validation approaches such as Fantini scale is used for questionnaire validation, Cronbach's Alpha to validate the reliability and metrics to validate the intra and inter cluster validity and Pearson correlation for validating the correlation among the variables.

Higher education students ICC three dimensions analysis

Table 4 displays the results of the examination of the attitude, knowledge, and skill aspects. The data analysis reveals that there is a significant positive correlation among the four dimensions of attitude, knowledge, consciousness and skill and students' ICC. These three dimensions have varying degrees of correlation with intercultural communicative competence. The correlation among the Knowledge and ICC is 0.972 indicates a very strong positive linear relationship between these two variables since the value is closer to 1, the correlation among the attitude and ICC is 0.835, the correlation among the Skill A and ICC is 0.885, the correlation among Skill B and ICC is 0.823, the correlation among consciousness and ICC is 0.714. Overall the correlation ranges from 0.7 to 1 that indicates the strong association among the considered dimensions of overall ICC level. The factors are interacts with each other and it follows the order knowledge > > Skill A > attitude > Skill B > consciousness.

The evaluation of 240 participants of ICC is illustrated in Fig. 4. The reference value is in the range 0 to 1, and the ICC mean value thorough evaluation of 240 chosen students is 0.4952.According to the evaluation of each ICC individual index, the total sample score for foreign cultural understanding is 0.0982, meaning that the data is extremely poor and insufficient. Nonetheless, the CCC skills score is 0.1314, and the reference value is in the range 0 to 0.25; the NCK score is 0.0286, and the difference value is in the range 0 to 0.05.

According to the study, 38 students who received a CET-4 score of 600 or higher underwent the ICC extensive estimate, and the findings of each index's comprehensive evaluation were comparable to the general circumstances of the 240 samples examined above. Furthermore, despite having outstanding foreign language CET-4 results, they have not improved their language proficiency. Table 5 shows the distribution of samples considered for survey.

Factors	Attitude	Knowledge	Skill A	Skill B	Consciousness	Overall level of ICC
Attitude	1	0.475**	0.325**	0.321**	0.228**	0.835**
Knowledge	0.475**	1	0.685**	0.682**	0.562**	0.972**
Skill A	0.325**	0.685**	1	0.625**	0.454**	0.885**
Skill B	0.321**	0.682**	0.625**	1	0.621**	0.823**
Consciousness	0.228**	0.562**	0.454**	0.621**	1	0.714**
Overall level of ICC	0.835**	0.972**	0.885**	0.885**	0.714**	1

Table 4. Analysis of ICC four dimension. (Note: the significance level is shown by the values ***, **, and *, which stand for 1%, 5%, and 10%, respectively).

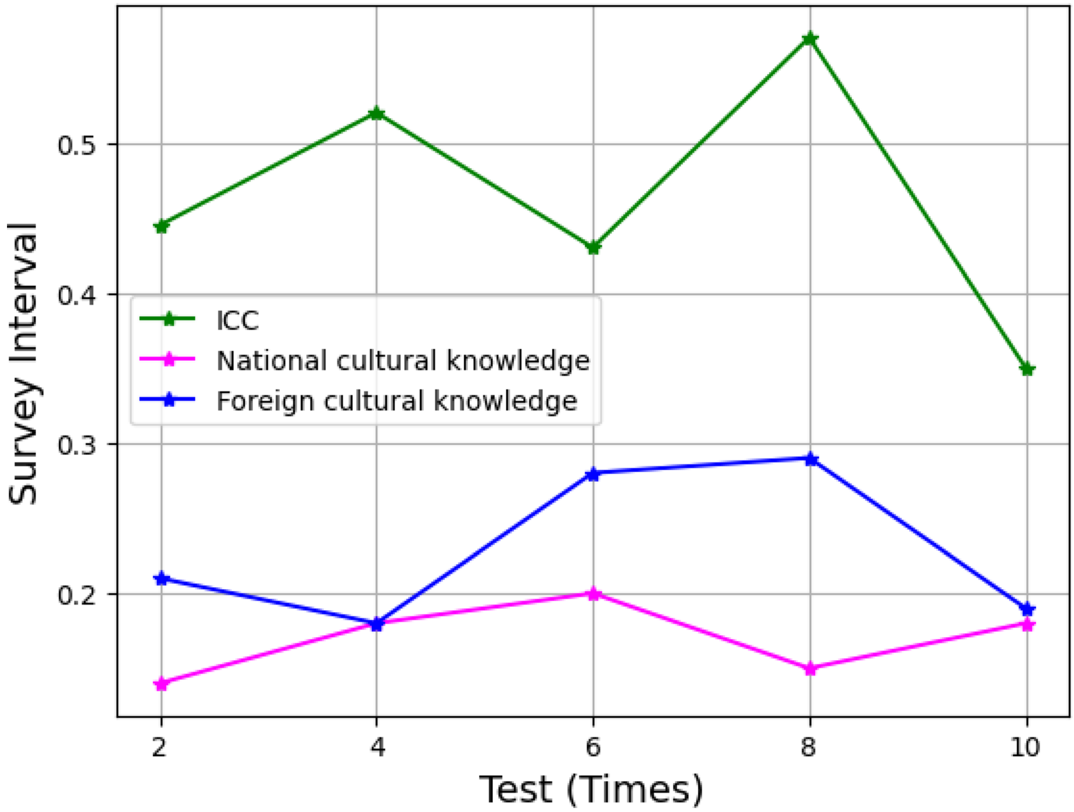

Fig. 4. ICC evaluation using fuzzy (Considered Samples: 240 peoples).

Factors	Min	Max	Mean
ICC evaluation	0.27	0.91	0.5232
National_cultural knowledge (NCK)	0.01	0.06	0.0288
Foreign_cultural knowledge (FCK)	0.03	0.28	0.1079
Attitude	0.09	0.18	0.1346
Intercultural_communication skills (IcC)	0.04	0.24	0.1396
Cross cultural cognitive skills (CCC)	0.02	0.06	0.0298
Consciousness	0.06	0.17	0.0878

Table 5. Considered data samples distribution.

There are 38 persons had CET-4 values higher than 600.Their comprehensive ICC evaluation average is 0.5232, that is greater than 0.5, and its ICC is marginally more than the norm.The value for reference is in the range 0 to 0.3, and the FCK score is 0.1099. The higher education students with a score of more than 600 on the CET-4 demonstrate a severe lack of FCK, and their particular ICC score indicators (history and geography abroad) are poor. They also have relatively weak social and political knowledge and a rudimentary understanding of CCC techniques. The reference value falls between 0 and 0.05, while the NCK score is 0.0288.Conversely, the value of is in the range 0 to 0.19, while the sample's attitude score is 0.1346.The score is superior middle, meaning that students with a score of 600 or more are at a higher level and have strong cross-cultural attitudes, including the ability to communicate over obstacles like racism and inter cultural flow willingness and interest.

There are 170 individuals have scores in the range of 490 to 599.Their average ICC evaluation is 0.4999, which is near 0.5.The FCK score is 0.0984, and the difference value falls between 0 and 0.30. The students who score between 490 and 599 on the individual ICC indices demonstrate a very poor command of foreign cultural knowledge. Additionally, the value is typically low. Table 6 displays the thorough assessment of 170 college students' cross-cultural competency.

There are 32 people have fourth-grade scores that are lower than 489.Their mean ICC assessment is 0.37, meaning a little below 0.5, and their ICC is slightly below the general level. The averages of each ICC individual index are often low, and college students who score lower than 489 demonstrate a very poor command of FCK. The reference value falls between 0 and 0.30, and the FCK score is 0.2512. However, the CCC skills score is 0.318 with a value ofreference is in the range 0 to 0.35. The four abilities listed above have mediocre scores. The

Factors	Min	Max	Mean
ICC evaluation	0.47	0.92	0.5449
NCK	0.01	0.06	0.0488
FCK	0.03	0.49	0.1084
Attitude	0.09	0.18	0.1246
IcC	0.03	0.44	0.1298
CCC skills	0.01	0.06	0.0492
Consciousness	0.06	0.17	0.0882

Table 6. ICC fuzzy comprehensive evaluation of 170 higher education students.

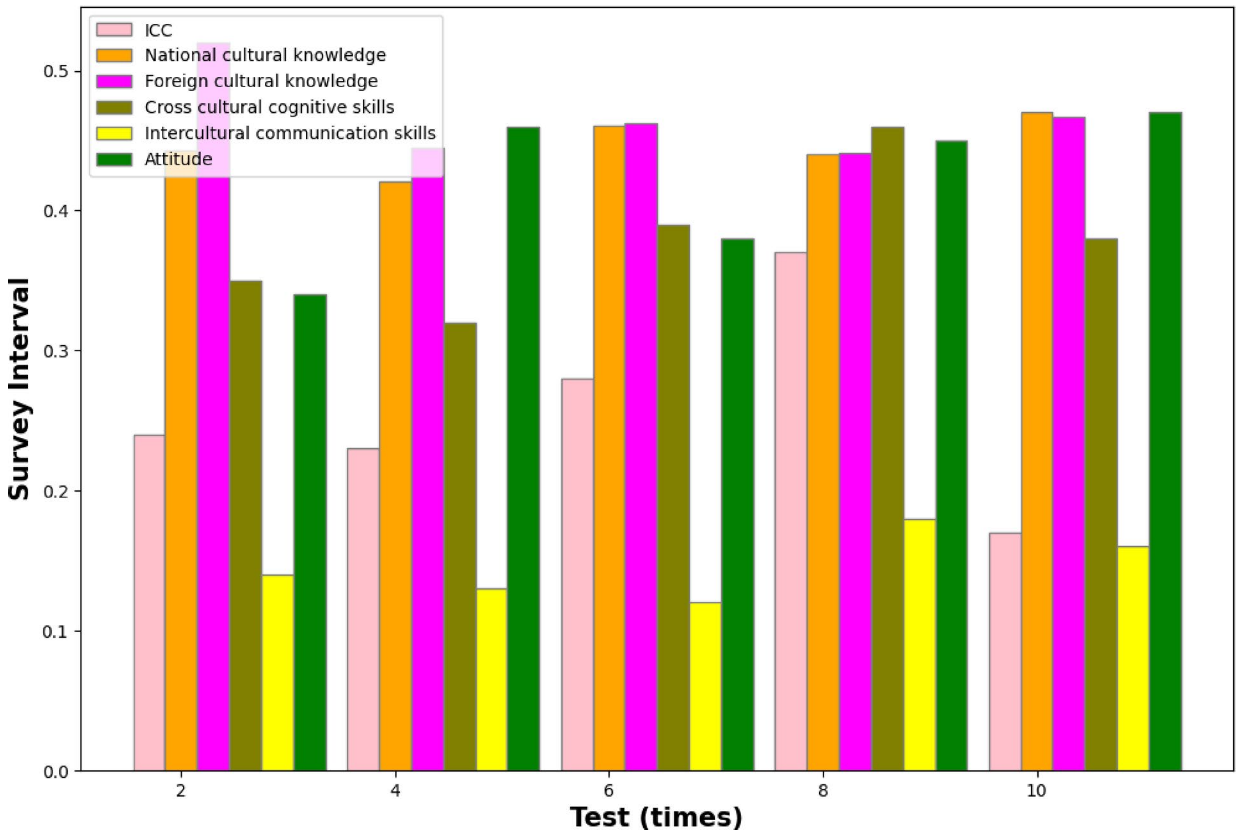

Fig. 5. Student evaluation with the grades less than 489.

aforementioned fourabilities have mediocre scores. Figure 5 displays the evaluation of pupils in the sample who scored 489 or lower on the Incet-4 scale.

According to the computation findings and illustrated in Fig. 6 for the impact of CCC competence, the ICC evaluation model, the majority of people have extremely low levels of foreign cultural awareness, and the ICC capabilities of the chosen samples are at a common level. In the middle are ability, skills, and consciousness. Conversely, they possess the most powerful attitudes. Additionally, the CET-4 performance factors demonstrate that a positive change in performance is accompanied by a correspondingly favorable change in the ICC level. They are all at the medium level, though, and the fluctuation range is not that wide.

There is a substantial two-sided correlation at the 0.01 level between the 240 participants' CET-4 values and their ICC comprehensive evaluation scores, with a correlation coefficient of 0.179. College students' language proficiency and their intercultural competency (ICC) are generally mutually enhancing. In Fig. 7, the importance evaluation is displayed.

Conclusion

When teaching artificial intelligence, it's critical to foster pupils' creativity. In order to satisfy cross-cultural needs, the performance evaluation concept in process evaluation is appropriately implemented based on these principles and tactics, guaranteeing that teaching evaluation truly contributes to feedback control and teaching impact optimization. Through the examination of the questionnaire results, the current status of intercultural

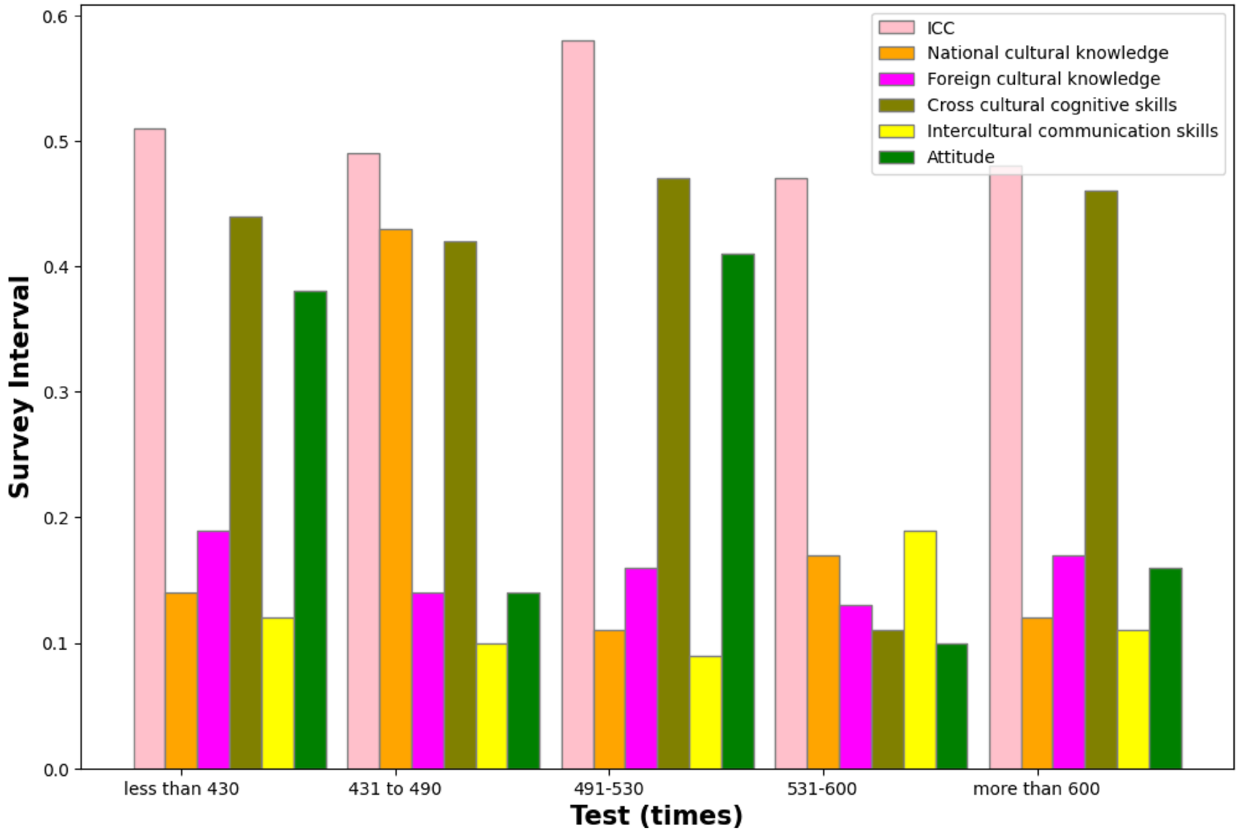

Fig. 6. Various ICC competence and CET 4 performance.

communication and understanding (ICC) in higher education and universities, the relationship among intercultural awareness and intercultural pragmatic ability, and the possible influence of intercultural adaptability on intercultural pragmatic competence were all investigated. The work outlined the history and objectives of universities' worldwide talent training programs. Second, a new research path reference was made available so that researchers could examine ICC and examine important elements (knowledge, skills, consciousness, and attitude). According to the four dimensions of ICC, awareness comes after knowledge, skills, attitude, and skills. The average range of "very inconsistent" and "relatively inconsistent" alternatives in each question was 0–8%, indicating that students' perceptions toward ICC were generally better than their attitudes toward ICC skills. Students received assistance with translations and cross-cultural references by utilizing the AI's capabilities.

Implications

The research illustrates that AI algorithms like Apriori, SimRank, Modified K-means, and Fuzzy logic can be used successfully to model and evaluate Intercultural Communicative Competence (ICC) in technical Education. This indicates a potential interdisciplinary frame-work that combines computational accuracy with qualitative human abilities.Through the correlation of teaching activities with ICC results, the proposed framework can guide curriculum development and instructional strategies in technical education. Institutions are able to use this model in order to discern which teaching interventions best promote students' intercultural awareness and skills. The fuzzy comprehensive assessment model enables educational researchers and administrators to numerically quantify vague and subjective characteristics such as attitude, consciousness, and cultural sensitivity providing a scalable method of measurement. The classification of students as per ICC-related attributes using Modified K-means suggests the promise of customized learning paths or focused training by students' inter-cultural needs and shortcomings. The correlation observed between CET-4 English exam scores and ICC levels lends support to the pedagogical principle that language acquisition complements intercultural competence and vice versa—useful for planning a language curriculum. The limitation of this study is the size of considered data samples. The sample, while large ($n = 1050$), is taken from a single national context (presumably China), restricting cross-cultural generalizability of results. Cultural subtleties in the expression of ICC are not accounted for in model interpretation. In conclusion, it is our responsibility as scholars and educators to shape and modify our approaches in order to fully utilize digital technologies while maintaining the rich human component of interpersonal relationships and our varied cultural legacies by considering the large volume of data.

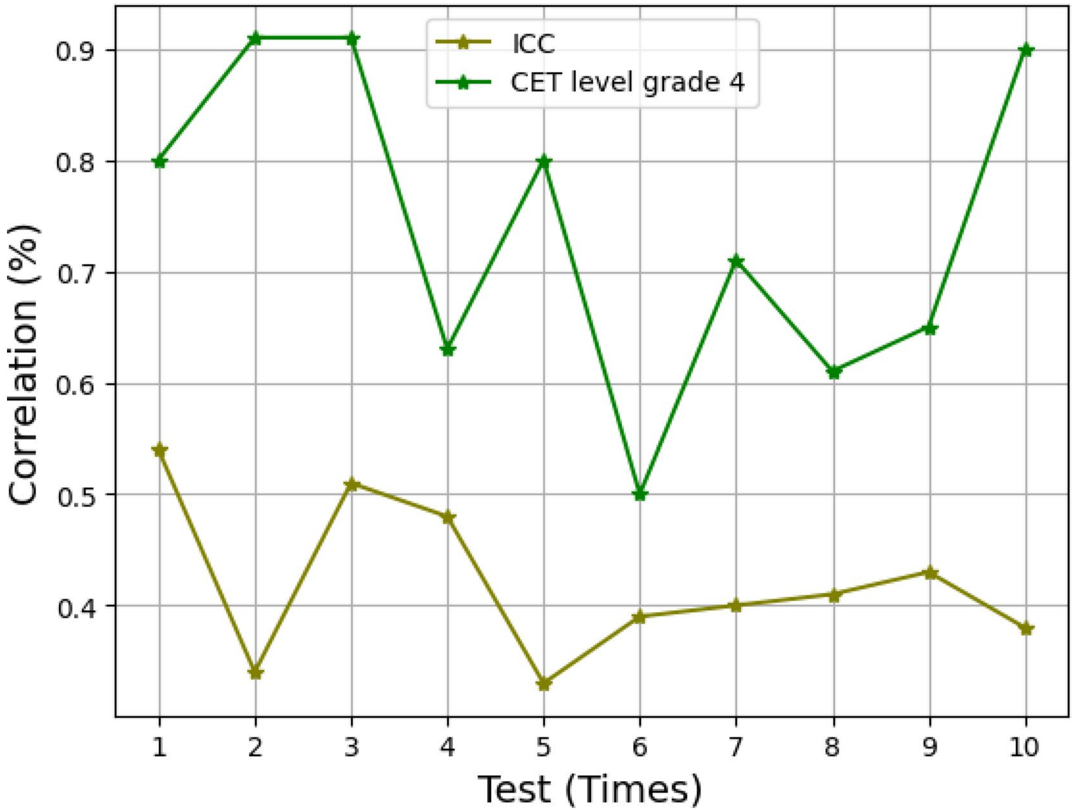

Fig. 7. Significant evaluation.

Data availability

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

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Author contributions

Q.Z. contributed to the conceptualization, methodology, data collection, formal analysis, and writing of the original draft. M.I.R.M.I. was involved in conceptualization, supervision, and reviewing and editing the manuscript. A.R.B.Z. contributed to supervision, validation, reviewing and editing, and funding acquisition. All authors have read and approved the final manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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