Generative AI with ensemble machine learning framework for computer science graduates employability prediction using educational big data

Vikas Rattan[1], Ruchi Mittal[1] and Jaiteg Singh[1]

[1] [1]Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, India

E-mail address: vikas.rattan@chitkara.edu.in, ruchi.mittal@chitkara.edu.in, jaiteg.singh@chiitkara.edu.in

Abstract: The employability of graduates has become a measure, for institutions because of the increasing number of graduates entering the job market and the intense competition for good job opportunities. Many studies have attempted to predict student's employability before they graduate using intelligence methods. However implementing these methods has proven to be time consuming and challenging requires effort with results so far. To address these challenges we propose a technique to identify the factors that impact the employability of computer science graduates and develop a model for predicting employability. We start by using exploratory factor analysis (EFA) to identify factors that affect the employability of computer science graduates, such as thinking and emotional intelligence. Then we use confirmatory factor analysis (CFA) to validate and evaluate these factors obtained from EFA. Additionally we create a two level model for employability prediction by combining based machine learning (ML) with generative artificial intelligence (AI). In the level of prediction we utilize ML techniques, like random forest, k nearest neighbor, decision tree and logistic regression. The performing model, from the stage is then used in the second stage of prediction. Here a generative multi-in-one artificial neural network (GMA-NN) calculates the employability prediction. Finally, the study formulates a contingency matrix for employability using the identified design factors and evaluates the model's performance and effectiveness using various design metrics. Our results indicate that the LR+GMA-NN model we propose achieves the highest accuracy at 97.846%, surpassing the existing state-of-the-art model by an impressive efficiency gain of 4.398%.

Keywords: ensemble machine learning, artificial intelligent, employability, computer science graduates, educational big data

1. Introduction (Heading 1)

In today's highly competitive environment, educational institutions have evolved from being mere providers of education to functioning as professional bodies that prepare students to be more employable and well-prepared for the demands of various industries [1][2]. The ultimate purpose of collecting and analyzing such data is to predict a student's employability accurately, enabling timely interventions and corrective measures to enhance overall student performance [3].Graduate employability refers to the degree to which individuals who have successfully completed higher education or training programs possess the necessary skills, knowledge, attributes, and qualities to make them attractive and competent candidates for employment opportunities in the job market [4]. In a broader context, higher education has a direct or indirect impact on a country's national economy by supplying a skilled workforce to various industries [5].The concept of graduate employability holds immense significance in today's world for several compelling reasons [6]. Moreover, graduate employability directly addresses the pressing issue of graduate unemployment [7][8]. By aligning their educational programs with the demands of the job market, institutions can uphold their reputation and provide value to students [9]-[12].

A predictive employability detection model is a comprehensive system [13]-[15] designed to assess and forecast the employability of individuals by considering various factors and attributes. The employment landscape is increasingly relying on data mining techniques [16] to extract valuable insights and patterns from extensive datasets encompassing individuals' qualifications, skills, and attributes. The predictive accuracy of student employability is further improved by incorporating additional characteristics, such as individual, social, emotional, and environmental variable star, into the dataset [17]. In one instance, a decision tree [18] is utilized to envisage the employability of apprentice engineering schoolchildren, helping identify the most suitable algorithm for this particular challenge. In this context, machine learning algorithms are employed to construct a predictive model aimed at forecasting the employability of information technology graduates, aligning their skills with the demands of the labor market [19]. The graph convolution network (GCN) [20] is used to gain understanding of graduates' strengths and weaknesses within the employment landscape.

2. Our Contributions

First, confirm that you have the correct template for We introduce a comprehensive framework designed for the evaluation of graduate employability factors, coupled with an ensemble machine learning approach integrated with a generative artificial intelligence-based predictive model for employability. The significant contributions of our proposed framework are delineated below:.

1. Exploratory factor analysis (EFA): We commence by conducting an EFA, a statistical technique, to identify and gain insights into the underlying factors or constructs that potentially influence employability. This analysis encompasses various factors, including emotional quotient and computational thinking skills.

2. Confirmatory factor analysis (CFA): Following the EFA, we employ a CFA to rigorously assess how well the identified factors derived from the initial analysis align with their corresponding theoretical constructs.

3. In the first level, we leverage ensemble machine learning systems, namely random forest, k-nearest neighbor, decision tree, and logistic regression, to generate predictions.

4. In the second level of prediction, we employ a generative multi-in-one artificial neural network (GMA-NN). This advanced neural network computes the final employability prediction, incorporating the insights and information gathered from the earlier stages of analysis and prediction.

The rest of the paper is organized as follows. Section 2 provides a brief overview of related work on evaluation of graduate employability factors and predictive model for employability detection. Section 3 describes the proposed framework in detail, including factors identification, factor validation, first level and second level prediction model. Section 4 provides the experimental results and discussion, and Section 5 concludes this paper.

3. RELATED WORK

In this segment, we present a literature review focused on the application of data removal systems for forecasting graduates employability. Table 1 provides a concise overview of the identified research gaps that have been gleaned from an extensive review of existing state-of-the-art methodologies.

3.1 State-of-art works

Yao et al. [21] introduced an approach for forecasting university students' employment rates based on the gray scheme methodology. They conducted a comprehensive analysis of the existing research landscape concerning college students' employ rate estimate and identified the sources of prediction blunders. The method achieved average accuracy rate of 95.22%, surpassing the performance of previous models with accuracy rates of 92.3% and 87.7%. Dongrui et al. [22] devised an approach for foreseeing the rational health status of alumnae. By pinpointing students who may be experiencing mental health challenges, this approach enables the provision of targeted care, guidance, and psychological intervention to prevent such issues from the health status.

Saidani et al. [23] have presented an efficient approach for forecasting student employability by incorporating contextual factors and employing Gradient Boosting classifiers. The findings indicated that the application of light gradient boosted machine classifier, particularly in the context of internships, yielded the most favorable results compared to the student-specific context. Wang et al. [24] have proposed a prediction model based on a support vector machine (SVM) that incorporates modifications using improved butterfly optimization method with communiqué and Gaussian bare-bones mechanism (CBBOA). CBBOA-SVM, coupled with a feature collection model, is advanced to forecast the upcoming career choices of college students. This approach not only assists unemployed college graduates in identifying suitable career paths but also aids the government in managing the broader employment market for college students. Smirani et al. [25] have introduced the stacked generalization for failure prediction (SGFP) model aimed at enhancing scholars' academic performance. SGFP achieves mean and median accuracies, effectively identifying student classifications with an average sensitivity of 97.3% and average precision of 97.2%.Mpia et al. [26] have presented an innovative deep stacking prognostic model, which incorporates five distinct multilayer perceptron (MLP) sub-models. The deep amassing model exhibited strong presentation metrics, including an accuracy rate of 80%, precision of 81%, recall of 80%, and an f1-score of 77%.Cheng [27] introduces the deep-seated neural network with robust education capabilities and flexibility designed for envisaging the employ outcomes of university students. Wang [28] presents a prediction model for the employ confidence index of college students. This model combines the gray model and BP neural network (GM-BPNN) while considering subjective employment obstacles and related predictive factors for college students. Bai et al. [29] have introduced a modified model, combining the deep belief net and softmax regression (DBN-SR), for predicting student employability. The employability calculation model achieves an accuracy rate exceeding 98%, which is notably 2.5% to 5% higher than models based on deep auto-encoders and deep neural networks. Alkashami et al. [30] have tackled the employability challenge in Mid-Eastern countries by employing an adaptive neuro-fuzzy inference system (ANFIS) data removal approach. Findings indicated that while ANFIS achieved an impressive 94% accuracy for the alumna dataset, it also displayed high complication due to the extensive use of qualities [43].

3.2 Problem statement

In India, employability challenges for recent computer science graduates persist, yet there is a notable shortage of scholarly research in this specific context. This study takes a unique approach by investigating how emotional quotient and computational thinking skills collectively influence the employability of computer science students in India. Through an extensive literature review using keywords are data mining, employability, CT and EQ. We have identified several unexplored research gaps, which we will elaborate on in detail:

- While certain studies have separately investigated the influence of emotional quotient on employability or the impact of CT on employability. What is currently lacking is a comprehensive study that considers three constructs, EQ, CT, and employability, in the specific setting of India.
- After an extensive review of existing academic literature, it became evident that there is a notable absence of relevant and substantial peer-reviewed studies that investigate the influence of EQ and CT on the employability of engineering students.
- Numerous predictive models have been devised to assess the employability factors of engineering students, use range of supervised and unsupervised learning. However, an intriguing observation from the existing literature is the absence of any predictive model that comprehensively integrates the influence of EQ and CT on the employability of computer science graduates.

Table1 Summary of Research gaps

Ref.	Methodology	Technique used	Factors used	Findings	Research gaps
[21]	Prediction of students' employment rate	Gray system	Economy, policy	Accuracy 95.22%	The challenge of significant errors in estimating employment rates
[22]	Mental health prediction of students' employment	Adaboost, Decision tree	Learning rate, technical skills	Accuracy 80.08%	Classifier accuracy affected by imbalanced rates
[23]	Predicting student employability	XGBoost, CatBoost, LGBM	Hard and soft skills	Accuracy 76%	High error rates in weak learners
[24]	Predicting college student career decisions	CBBOA-SVM	Computational thinking	Accuracy 94.2%	Transparency and reliability issues arising from secondary data sources
[25]	Predict student failure	LGBM, XGB, and RF	Computational thinking	Success rates 98.86%	Limitations in overall detection rates due to multiple hidden layers
[26]	Predict employability of Congolese information	Deep stacking predictive model	Social and entrepreneurial experience	Accuracy 80%	Difficulty in generalizing mitigation measures due to inconsistency factors
[27]	Employment data screening, prediction	Deep seated neural network	English proficiency	Accuracy 94.9%	Inability to capture linear variation patterns in students
[28]	Employment obstacle of college students	GM-BPNN	Software and computational thinking	Accuracy 85.23%	Complex prediction models with time-dependent solutions
[29]	Predicting student employability	DBN-SR	Course type, skills	Accuracy 98%	Insufficient consideration of relevant factors for employability prediction
[30]	Predicting early employment readiness	Adaptive neuro-fuzzy inference system (ANFIS)	Computational thinking	Accuracy 94%	Susceptibility to overfitting, noise interference, and reduced prediction capability

- Within the existing body of literature, numerous researchers have separately delved into the exploration of EQ factors, while others have dedicated their efforts to understanding CT. The literature reveals conspicuous absence of investigations into the potential interplay between EQ and CT.

4. Proposed methodology

The proposed framework for employment prediction encompasses a series of meticulously structured steps as shown in Fig. 1 to ensure the accuracy and reliability of its predictions. It initiates with the vital phase of data collection, focusing on Computer Science graduates in their final year of studies from renowned institutions in Delhi, Bangalore, and Hyderabad, which are celebrated for their technological prominence. Following data collection, data preprocessing step is executed to eliminate any unwanted artifacts or noise, guaranteeing the integrity of the subsequent analyses. Subsequently, the data is partitioned into appropriate subsets to facilitate effective organization and analysis. The core of the framework lies in its application of exploratory factor analysis (EFA) to the partitioned data. Within this process, principal component analysis (PCA) is employed, incorporating orthogonal rotation, specifically the Varimax method. This rotation technique enhances the interpretability of the derived factors. To maintain a focus on robust factors, items with standardized factor loadings below 0.4 are disregarded. EFA serves the pivotal role of unveiling employability factors embedded within the dataset, teasing apart emotional quotient (EQ) and computational thinking (CT) as distinct elements. To ensure the soundness of the factors identified through EFA, the data undergoes confirmatory factor analysis (CFA). The subsequent phase involves the application of an ensemble predictive model, designed to harness the predictive strengths of multiple algorithms. Ensemble learning follows, with the first layer of the model integrating various classification algorithms, including random forest [44], decision tree, k-nearest neighbor (K-NN), and logistic regression. From this array of first-layer predictions, the framework carefully selects the best-performing classifier solution. The final step culminates with the generative multi-in-one artificial neural network (GMA-NN), which takes the baton from the previous layer's top-performing classifier. This neural network refines the predictions further and furnishes the conclusive employment prediction solution for computer science graduates.

4.1 Data collection and pilot study

A pilot test is an essential preliminary step that aims to gauge the feasibility of addressing the main research questions effectively while also evaluating the functionality and reliability of the questionnaire in use. In this context, we selected group of 47 Computer Science graduates and professionals were identified to participate in the pilot study. Incorporating the valuable feedback from the pilot training, several refinements were familiarized to the questionnaire. These modifications stayed instrumental in fine-tuning the questionnaire, enabling it to aptly capture essential data related to the employability factors of computer science graduates. Subsequent to the pilot study and the questionnaire refinements, data collection encompassed both EQ and CT. Each of these factors consisted of a set of questionnaires, as illustrated in Tables 2 and 3.

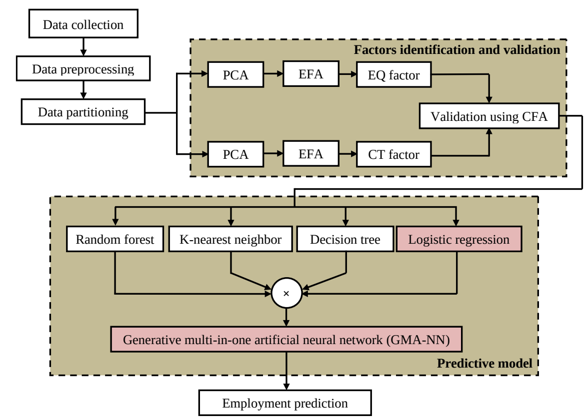


Fig. 1 Overall conceptual structure of proposed framework for employment prediction for computer science graduates

4.2 Exploratory factor analysis (EFA)

An exploratory factor analysis (EFA) seeks to uncover the latent structures within the dataset, offering an initial glimpse into potential patterns. EFA is potent statistical method when handling numerous variables [31]. This perspective aligns with the viewpoint of [32], identified EFA as a valuable technique for interpreting complex multivariate associations. Further EFA is adept at pinpointing clusters of closely correlated variables. This method not only streamlines the number of variables but also yields factor loading scores, signifying the relationship between a variable and its corresponding factor.

4.2.1 Kaiser Meyer-Olkin (KMO) and Bartlett's test

Adequacy of the research example is essential for applying factor analysis. The KMO test ensures this by examining the sufficiency of sample observations [33][34]. Hence, before embarking on factor analysis, one must first ascertain sample adequacy with the KMO test and validate variable correlations using the Bartlett's Sphericity Test. To be considered significant, the KMO test's value should exceed 0.60 [33][34]. Additionally, we suggest that a p-value below 0.05 indicates the adequacy of the Bartlett's Sphericity test. Meanwhile, a factor loading value above 0.5 is deemed meaningful [32].

4.2.2 Factor extraction using principal component analysis (PCA)

The process of factor extraction using PCA generally unfolds in the following steps:

• Data Preparation: The journey commences with a dataset comprising multiple variables, often denoted as features or attributes.

• Correlation Matrix: The initial step involves the calculation of a correlation matrix for the dataset, which essentially quantifies the relationships existing between variables.

• Eigen value Decomposition: PCA leverages an eigen-value decomposition, to deconstruct the correlation matrix into its constituent components. This procedure yields a set of eigenvectors and eigenvalues.

• Eigenvectors and Eigenvalues: In this context, eigenvectors function as representations of directions or axes within the original variable space.

• Principal Component Selection: The eigenvectors are then arranged in descending order based on the eigenvalues they are associated with. Principal components linked to the highest eigenvalues are capturing the most variance present within the original data.

• Factor Extraction: The principal components that are retained essentially serve as the extracted factors. These factors are essentially linear combinations of the original variables and hold the distinctive characteristic of being orthogonal, meaning they are uncorrelated to one another.

• Data Transformation: The final step involves the transformation of the original dataset into a new dataset. Importantly, this transformed dataset retains a significant portion of the variability that was initially present in the original data, albeit with a significantly reduced number of variables.

Table 2 Statements measuring CT factor

Items	Statements	1	2	3	4	5
Creativity	I like people who stick to most of their decisions					
	I like realistic and neutral people					
	I believe that if I put in enough time and effort, I can solve most of the problems I face.					
	I am confident that I can solve the problems that may arise in a new situation.					
	I hope I can use the program to solve my problem.					
	The dream leads to the coverage of my most important projects.					
	I trust my instincts and sense of "right" and "wrong" when approaching a problem.					
	When faced with a problem, I think about that problem before moving on to something else					
Algorithmic Thinking	I can immediately identify the capital that solves the problem					
	I think I am particularly interested in mathematical processes					
	I think I learn instruction better with the help of mathematical symbols and concepts					
	I believe I can easily capture the relationship between figures					
	I can mathematically express solutions to problems I encounter in my daily life.					
	I can digitize a verbal math problem					
Cooperativity	I love learning cooperatively with my group of friends					
	In cooperative learning, I think working in a group is more successful.					
	I like solving group project problems in cooperative learning with friends					
	More ideas occur in supportive learning					
Critical Thinking	I am good at making routine plans to solve complex problems					
	It is fun to try to answer the compound difficulties.					
	I am enthusiastic to learn stimulating things					
	I pride myself on being able to think so precisely					
	I use a systematic method when comparing the options at hand and making a decision					
Problem Solving	I have trouble seeing the solution to the problem in my mind					
	I am having trouble where and how to use variables like X and Y to solve the problem.					
	I cannot use the solutions that I plan systematically and step by step					
	I can't generate many options when thinking about possible solutions to a problem.					
	I cannot generate my own ideas in a collaborative learning environment					
	I am tired of learning things with my group friends in cooperative learning					

4.2.3 Rotation using Varimax with Kaiser Normalization

Rotation using Varimax with Kaiser Normalization is a statistical technique used to enhance the interpretability of the extracted factors or components. After performing an initial factor extraction, rotation methods like Varimax with Kaiser Normalization can be employed to simplify and clarify the structure of the factors.

4.3 Confirmatory factor analysis (CFA)

Table 3 Statements measuring EQ factor

Items	Statements	1	2	3	4	5
Interpersonal	Can't come up with a quick one					
	Others must create results					
	Difficult to compute optimal solution					
	Refine talent program					
	Difficult to accept the target results					
	Random solution acceptance					
	Leader must follow rules					
	Think of confident solution					
	Must understand the feelings					
	Concentrate on up/down solution					
Intrapersonal	Difficult to accept the target results					
	Refine talent program					
	It's good to think about how others feel					
	Difficult to accept friends feeling					
	Consider what happens to others					
	Close connections make sense					
	Focused on others					
	Difficult to accept the false commitment					
	Need to accept the good relationship=					
	Accept the social thinning					
Adaptability	Consider solution as per flow					
	Avoid the day dreamer					
	Consider problematic case and provide solution for that					
	Confident with background before solving problem					
	Must think and work out before selects option					
	Difficult to accept first option in mind					
	Workout answer based on the options					
Stress Management	Need anger management					
	Maintain the anger control flows					
	Anxiety can be difficult to control					
	Define anger ion different actions					
	Find suitable solution for anger management					
	Check control measure including stress					
	Consider solution for temper management					
	Check temper and anger issue					

Confirmatory factor analysis (CFA) is a sophisticated arithmetical technique used to evaluate the alignment between observed data and predefined measurement model [35]-[38]. Unlike exploratory factor analysis, which aims to uncover latent structures within data without any predetermined assumptions, CFA requires researchers to stipulate in advance the number of factors and how observed variables relate to these factors [39]. This makes CFA a stringent test of a given theory: it allows researchers to determine whether the data aligns with the anticipated factor structure, which is often based on prior research or theoretical foundations [40[41]. The process entails the examination of various fit indices, factor loadings, and modification indices to ensure the adequacy of the model [42].

4.4 Employability predictive model

We construct a dual-tier predictive model tailored for employability prognosis, leveraging the factors we have identified. In the initial prediction tier, we employ an ensemble of machine learning techniques such as random forest, decision tree, k-nearest neighbor, and logistic regression. From this ensemble, we select the most adept model based on its performance. This chosen model advances to the second prediction tier, where it interfaces with generative multi-in-one artificial neural nets (GMA-NN) to generate the ultimate employability prediction.

4.4.1 Ensemble of machine learning

• Random forest: It's a collective learning system that builds manifold decision trees during training and syndicates forecasts to progress accuracy and reduce overfitting [43]. Here, it is used to analyze the relationships between EQ, CT, and employability factors. Each decision tree in the forest considers different combinations of EQ and CT attributes and contributes to the employability prediction.

• k-nearest neighbor (k-NN): It's a managed learning algorithm used for classification tasks. For employability prediction, k-NN can be applied by measuring the similarity between the EQ and CT attributes of a student and those of other students in the dataset. The algorithm calculates the 'k' nearest neighbors and predicts employability based on the majority class among these neighbors. This approach assumes that graduate with similar EQ and CT profiles are likely to have similar employability outcomes.

• Decision tree: It is used to create a hierarchical structure of decision rules grounded on input landscapes. In the background of employability forecast, a decision tree can be built using EQ and CT attributes as input features. The tree is constructed by recursively splitting the data based on attribute values to predict employability outcomes. Each branch and node of the tree represents a decision rule based on EQ and CT attributes.

• Logistic regression: It is an arithmetical technique used for binary organization tasks, where the goal is to forecast one of two imaginable consequences. Here, it can be applied by modeling the relationship between EQ, CT, and employability as a logistic function. The model estimates the likelihood of a student being employable grounded on their EQ and CT attributes.

4.4.2 Generative multi-in-one artificial neural network (GMA-NN)

In second level model, we utilize a generative multi-in-one artificial neural network (GMA-NN) for the employability predictive model for computer science graduates. Let U_1^B us denote the un-encoded information sequence of the polar codes, and then u denotes the information bits with a subscript. For ease of calculation, frozen bits are usually set of values. The procedure of encoding technique using a specific lined block code is articulated as follows.

$$p_1^B = U_1^B J_B \quad (1)$$

where p_1^B is a coded arrangement, J_B is the group atmosphere of polar ciphers, which is definite as

$$J_B = N_B f^{\otimes b} \quad (2)$$

Where $b = log_2 B$, $f^{\otimes b}$ b-th order of Kronecker creation, and $f = \begin{bmatrix} 10 \\ 11 \end{bmatrix}$. For the stage t (t ⩽ b), the node $V_{(t,k)}$ characterizes the K-th node of the step t, which comprises $B/2^{t-1}$ -bit log likelihood ratio $\alpha_{(t,k)}$ and $B/2^{t-1}$-bit return material $\beta_{(t,k)}$. The left and right child nodes of node V can be distinct as V_l and V_R individually, and of and can be designed by

$$\alpha_{Vl}[h] = 2\, arctan\, i\left(tan\, i\left(\frac{\alpha_V[h]}{2}\right) tan\, i\left(\frac{\alpha_V[2h+1]}{2}\right)\right) \quad (3)$$

$$\alpha_{Vl}[h] = \alpha_V[2h](1 - 2\beta_{VL}[h]) + \alpha_v[2h+1] \quad (4)$$

where is $\beta_{VL}$the arrival substantial of node V_l. The cunning formulation of βv for the node V is as follows:

$$\beta_V[h] = \begin{cases} \beta_{VL}[h] \oplus \beta_{VR}[h], h \in \{1,3,\ldots.2^{t-1}-1\} \\ \beta_{VR}[h] h \in \{0,2,\ldots.2^{t-1}-2\} \end{cases} \quad (5)$$

Consequently, the only way to gain $\beta_V$is to β_{VL} and $\beta_{VR}$from its left and right child nodes conferring as follows.

$$\beta_{(b-1,K)} = \begin{cases} 1, \alpha_{(b-1,K)} < 0, K \in \wedge \\ 0, otherwise \end{cases} \quad (6)$$

The α_{Vl} and β_{VL}left child nodes are computed for each node of the second tree, so do α_{VR} and $\beta_{VR}$of the right child nodes from β_{VL} and β_{VR} are computed and β_v. The process of α_{Vl} executing a complex decision to obtain a value β_{VL}does not take a single time step, so three-time ladders are obligatory to compute a node.

$$\beta_v = i(\alpha_v) \quad (7)$$

where h (·) is the complex decision function. After receiving β_v, it is not necessary to calculate the α values of all child nodes -1, but the decoding result $\hat{u}_v$ should be calculated accordingly, where $J_{B/2^{t-1}}$ is the Kronecker product of $B/2^{s-1}$ -th order

$$\hat{u}_v = \beta_v J_{B/2^{t-1}} \quad (8)$$

The last child of the node representative is the node material bit and the others are freezing bits. Let node V be the k-bit node Rep, where the preceding k - 1 bits β_v are 0, shows β_V^K its k-bit appearance as follows.

$$\beta_V^K = \begin{cases} 0, \alpha_{sum} \geq 0 \\ 1, \alpha_{sum} < 0 \end{cases} \quad (9)$$

where $\alpha_{sum} = \sum_{h=1}^{K} \alpha_V[h], \hat{u}_h$ can I get direct For a node representative, only one α_{sum} time step is required in the computation process. Let α_{sum} node make a complex decision $I_\alpha[h]$ and let x denote the result of bitwise mod-2 addition to the data set $I_\alpha[h]$.

$$\beta_V[h] = \begin{cases} I_\alpha[h] \oplus x, h = g \\ I_\alpha[h], h \neq g \end{cases} \quad (10)$$

This $g = arg_h \quad min\,|\,\alpha_V[h]|$ method requires finding the smallest value of g in α_V the computation of where is the most unstable bit code, and the time period used is strong-minded by the amount of nodes it contains. The connection among the input V_{in} and output V_{out} of each nerve cell as follows.

$$V_{out} = Z \cdot V_{in} + n \quad (11)$$

where Z is the heaviness of the neuron and n is the balance value. Network learning is the process of changing w and b.

$$l(q,\hat{q}) = -\frac{1}{b}\sum_{h}^{\hat{\sum}_{h h}\widehat{log(h}} q_h log \tag{12}$$

During network training, the loss worth $l(q,\hat{q})$ of the current exercise example is computed the y value and the true value $\hat{q}$, where h represents the data index of the dataset. After gaining the loss worth, the stochastic incline descent technique and the inverse multiplication technique are used to appraise the z and n standards, so the network loss after appraising the weight worth is reduced in the calculation of the current exercise in the gradient direction.

$$\hat{u}_h = \begin{cases} 1, sigmoid(q_h) \geq 0.5 \\ 0, sigmoid(q_h) < 0.5 \end{cases} \tag{13}$$

The time steps used to compute a fully connected neural network $S_{BB} = S + 1$, S represents the amount of hidden coatings. For the polar code neural net, as the activation function of the network, the Relucan achieve the best decoding presentation of the polar codes, and the GMA-NN is used to decode the polar codes.

$$VS_{NSC} = \frac{B}{2^{t-1}}(S_{BB}+1) + 2\frac{B}{2^{t-1}} - 2 \tag{14}$$

The steps in the node V calculation process are to estimate the value of α1 and make a complex decision to obtain β1.

$$\beta[h] = \begin{cases} 1, \alpha[h] < 0 \\ 0, otherwise \end{cases} \tag{15}$$

After gaining of the solid conclusion value, $\hat{u}_1$ is intended conferring to

$$\hat{u}[h] = \begin{cases} \beta[h], h \in \wedge \\ 0, otherwise \end{cases} \tag{16}$$

The process of leaf node β for dissimilar nodes in the similar phase, but the calculation process of $\hat{u}$ is dissimilar from the derived β since the frozen bits and material bits are connected to diverse nodes. Algorithm 1 describes the steps involved in the employability prediction using GMA-NN.

Algorithm 1 Employability prediction for computer science graduates using GMA-NN

Input: Number of independent variables, maximum iteration, termination condition

Output: Dichotomous result (1/0, Yes/No, True/False)

1 Initialize the random population
2 Define encoding polar codes using specific linear block code $p_1^B = U_1^B J_B$
3 If i=0 , j=1
4 While **Do**
5 Compute βv for the node

$$V\ \beta_V[h] = \begin{cases} \beta_{VL}[h] \oplus \beta_{VR}[h], h \in \{1,3,\dots.2^{t-1}-1\} \\ \beta_{VR}[h] h \in \{0,2,\dots.2^{t-1}-2\} \end{cases}$$

6 The Kronecker product of $B/2^{s-1}$-th order $\hat{u}_v = \beta_v J_{B/2^{t-1}}$
7 The connection between the input V_{in} and output V_{out} of each neuron

$$V_{out} = Z \cdot V_{in} + n$$

8 Define the time step

$$S_{NSC} = \frac{B}{2^{t-1}}(S_{BB}+1) + 2\frac{B}{2^{t-1}} - 2$$

9 End if

10 Update the final value

11 End

5. Results and Discussion

In this section, we present the results and comparative analysis of proposed and existing state-of-art employability prediction models. Employing appropriate analytical methods, we scrutinize the data to uncover the intricate factors that impact the employability of computer science graduates. Our framework is implemented in the Google Colab simulation environment using the Python programming language. We validate the effectiveness of framework through a series of analyses, including EFA, CFA, and predictive modeling. Additionally, construct employability matrix through cross-tabulation, capturing the interactions and intersections of key factors in the employability context.

5.1 EFA analysis for CT factor

The table 4 presents the extracted factors related to CT using PCA and Varimax with Kaiser Normalization. These factors are instrumental in understanding the various dimensions of CT that influence the employability of computer science graduates. Creativity exhibits the highest initial eigen-value of 10.785, contributing to 37.188% of the total variance. As we progress through the components, the cumulative variance reaches 73.736% by the fifth component. Creativity is evidently significant dimension within CT and plays a pivotal role in employability. Algorithmic thinking demonstrates its importance, with a gradual decline in eigenvalues across its components, ultimately contributing to 1.688% of the total variance. While it may not be as dominant as Creativity, algorithmic thinking remains a relevant component of CT. Cooperativity showcases a similar trend, contributing to 1.199% of the total variance in its first component.

Table 4 Extract factors form CT using PCA and Varimax with Kaiser Normalization

Items	Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
		Total	Variance %	Cumulative %	Total	Variance %	Cumulative %	Total	Variance %	Cumulative %
Creativity	1	10.785	37.188	37.188	10.785	37.188	37.188	6.337	21.853	21.853
	2	4.061	14.003	51.192						
	3	3.065	10.569	61.761						
	4	1.89	6.519	68.279						
	5	1.583	5.457	73.736						
	6	0.658	2.27	76.006						
	7	0.598	2.063	78.069						
	8	0.518	1.787	79.856						
Algorithmic Thinking	9	0.49	1.688	81.545	4.061	14.003	51.192	4.151	14.314	36.167
	10	0.435	1.499	83.043						
	11	0.427	1.471	84.514						
	12	0.394	1.359	85.873						
	13	0.369	1.272	87.146						
	14	0.349	1.204	88.35						
Cooperativity	15	0.348	1.199	89.549	3.065	10.569	61.761	3.863	13.32	49.486
	16	0.328	1.13	90.679						
	17	0.317	1.093	91.772						
	18	0.301	1.037	92.809						
Critical Thinking	19	0.27	0.931	93.74	1.89	6.519	68.279	3.61	12.448	61.934
	20	0.255	0.879	94.62						
	21	0.252	0.868	95.487						
	22	0.231	0.796	96.283						
	23	0.195	0.673	96.956						
Problem Solving	24	0.186	0.643	97.599						
	25	0.164	0.564	98.163						
	26	0.162	0.559	98.722						
	27	0.15	0.516	99.237						
	28	0.118	0.408	99.645						
	29	0.103	0.355	100						

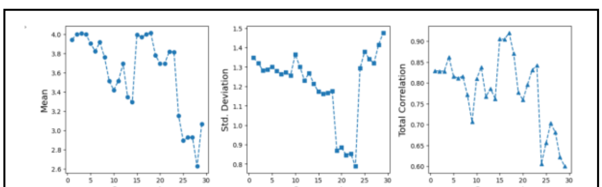


Fig. 2 Reliability statistics measure for CT factors.

The reliability statistics measured for the CT factors, as presented in Fig. 2, offer insights into the consistency and stability of these factors across the surveyed population of computer science graduates. The high Total Correlation values, average around 0.828, strong internal consistency among the items related to creativity, reinforcing its reliability as a factor contributing to CT in employability context. Mean scores for algorithmic thinking components (ranging from 3.294 to 3.693) reflect a moderate level of self-assessment by respondents regarding their algorithmic thinking skills. The standard deviation values suggest a reasonable degree of consistency in these assessments. The total correlation values, ranging from 0.707 to 0.837, indicate acceptable internal consistency, supporting algorithmic thinking as a reliable aspect of CT, albeit with room for improvement. The Mean scores for Cooperativity components (ranging from 3.971 to 4.015) signify that respondents generally perceive themselves as cooperative individuals within the context of CT. The low standard deviation values suggest a high degree of agreement among respondents regarding their Cooperativity. The notably high total correlation values, averaging around 0.900, underscore a strong internal consistency, affirming Cooperativity as a robust and dependable dimension of CT concerning employability. The Mean scores for Critical Thinking components (ranging from 3.695 to 3.821) indicate a moderate level of self-assessed critical thinking skills among respondents. The standard deviation values suggest relatively consistent assessments across the

Table 5 Extract factors form EQ using PCA and Varimax with Kaiser Normalization

Items	Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
		Total	Variance %	Cumulative %	Total	Variance %	Cumulative %	Total	Variance %	Cumulative %
Interpersonal	1	7.248	23.38	23.38	7.248	23.38	23.38	5.522	17.812	17.812
	2	6.147	19.828	43.208						
	3	4.844	15.626	58.834						
	5	2.181	7.035	65.869						
	6	0.763	2.461	68.33						
	7	0.721	2.326	70.655						
	8	0.686	2.212	72.868						
	9	0.61	1.967	74.834						
	10	0.568	1.833	76.667						
Intrapersonal	11	0.532	1.715	78.382	6.147	19.828	43.208	5.464	17.627	35.439
	13	0.517	1.669	80.05						
	15	0.492	1.587	81.637						
	16	0.48	1.547	83.185						
	17	0.435	1.403	84.588						
	18	0.429	1.385	85.973						
	19	0.408	1.315	87.287						
	20	0.372	1.199	88.486						
Adaptability	21	0.359	1.157	89.644	4.844	15.626	58.834	5.215	16.824	52.263
	22	0.349	1.125	90.768						
	23	0.332	1.071	91.839						
	24	0.317	1.022	92.861						
	25	0.306	0.987	93.848						
	26	0.298	0.963	94.81						
	27	0.278	0.898	95.708						
Stress Management	28	0.242	0.782	96.49	2.181	7.035	65.869	4.218	13.606	65.869
	30	0.232	0.747	97.237						
	31	0.222	0.715	97.952						
	32	0.21	0.676	98.628						
	33	0.196	0.633	99.261						
	34	0.136	0.438	99.699						
	35	0.093	0.301	100						

sample. The total correlation values, fluctuating from 0.759 to 0.842, signify reasonable interior steadiness, validating critical thinking as a reliable facet of CT contributing to employability.

5.2 EFA analysis for EQ factor

The extracted factors from EQ using PCA and Varimax with Kaiser Normalization are presented in Table 5. The variance reveals that these components contribute significantly to the overall variance, with cumulative of 76.667%. The high initial eigenvalues indicate that these components elucidate a substantial helping of the modification in EQ. The initial eigenvalues for the Intrapersonal components (ranging from 0.372 to 0.532) indicate the perceived importance of intrapersonal attributes related to EQ. While their contributions to variance are relatively lower, the cumulative percentage of 88.486% suggests that these factors are collectively significant. The initial eigenvalues for the Adaptability components (ranging from 0.317 to 0.359) demonstrate that respondents place importance on adaptability as an aspect of EQ, albeit to a slightly lesser extent than interpersonal and intrapersonal skills. The cumulative of 91.839% indicates overall significance of adaptability within EQ. The initial eigenvalues for stress management components (ranging from 0.093 to 0.242) reveal that respondents perceive stress management as a relatively less dominant factor within EQ. However, the cumulative of 96.49% underscores the collective significance of these components.

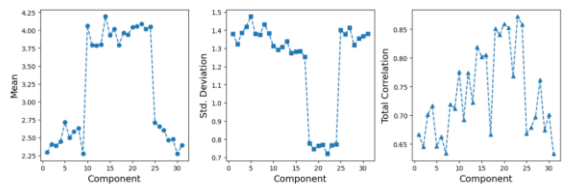


Fig. 3 Reliability statistics measure for EQ factors.

The reliability statistics for EQ factors are presented in Fig. 3. The reliability statistics for Interpersonal factors demonstrate high levels of interior constancy, as designated by Cronbach's Alpha standards fluctuating from 0.634 to 0.905. This implies that the matters effectively degree a cohesive hypothesis connected to interpersonal abilities, with an overall mean of 2.4675. Si milar to Interpersonal, the Intrapersonal factors exhibit high internal steadiness, with Cronbach's Alpha morals fluctuating from 0.667 to 0.929. The overall mean for Intrapersonal factors is 3.841, suggesting that respondents generally perceive themselves favorably in these areas. The Adaptability factors also demonstrate strong internal consistency, with Cronbach's Alpha values ranging from 0.840 to 0.955. This signifies that respondents' assessments of their adaptability skills are highly reliable and interrelated. The overall mean for Adaptability factors is 3.997, indicating that respondents perceive themselves as possessing relatively high adaptability. Within stress management factors, Cronbach's Alpha values range from 0.633 to 0.891, signifying good internal consistency. This suggests that respondents' self-assessments of their stress management abilities are reliable, converge to measure coherent construct. The overall mean for stress management factors is 2.588, implying that respondents perceive their stress management skills to be moderate.

5.3 CFA analysis for CT and EQ factors

The validity of the measurement model for CT and EQ factors, as presented in Table 6 and 7 respectively. The validity results for Creativity factor indicate that it exhibits a strong confident connection with itself, with a constant of 0.842. This suggests that the questionnaire items related to Creativity reliably measure this specific dimension of CT. Additionally, the composite reliability value of 0.924 signifies that the items within Creativity form a reliable and internally consistent construct. The amount of variance explained, 0.709, indicates that items collectively contribute significantly to the overall variance in the Creativity factor. Similarly, critical thinking demonstrates strong positive relationship with itself, with coefficient of 0.840, indicating that the items assessing this dimension are highly related. Cooperativity exhibits a strong positive relationship with itself (coefficient of 0.925), suggesting that the questionnaire items for this factor are closely related and reliably measure Cooperativity within CT. The high composite reliability value of 0.960 signifies strong internal consistency. The amount of variance explained, 0.856, underscores the importance of these items in capturing the overall variance in Cooperativity. Lastly, the validity analysis for problem solving indicates a moderate positive relationship with itself (coefficient of 0.708). This suggests that the items assessing problem solving are related and contribute to measuring CT dimension. The composite reliability value of 0.858 demonstrates good internal consistency. The amount of variance explained, 0.502, indicates that these items collectively contribute to the overall variance in problem solving.

Table 6 Validity of measurement model for CT factors

CT factors	**Creativity**	**Critical thinking**	**Algorithmic thinking**	**Cooperativity**	**Problem solving**	**Composite reliability**	**Amount of variance**
Creativity	0.842					0.924	0.709
Critical thinking	0.077	0.84				0.951	0.706
Algorithmic thinking	0.115	0.679	0.817			0.923	0.668
Cooperativity	-0.08	0.631	0.511	0.925		0.96	0.856
Problem solving	0.118	0.252	0.354	0.228	0.708	0.858	0.502

Table 7 Validity of measurement model for EQ factors

EQ factors	Adaptability	Interpersonal	Intrapersonal	Stress management	Composite reliability	Amount of variance
Adaptability	0.867				0.955	0.752
Interpersonal	-0.013	0.718			0.905	0.515
Intrapersonal	0.114	-0.024	0.791		0.93	0.625
Stress management	0.024	0.595	0.042	0.736	0.892	0.542

Table 8 Result comparison of predictive models for employability prediction

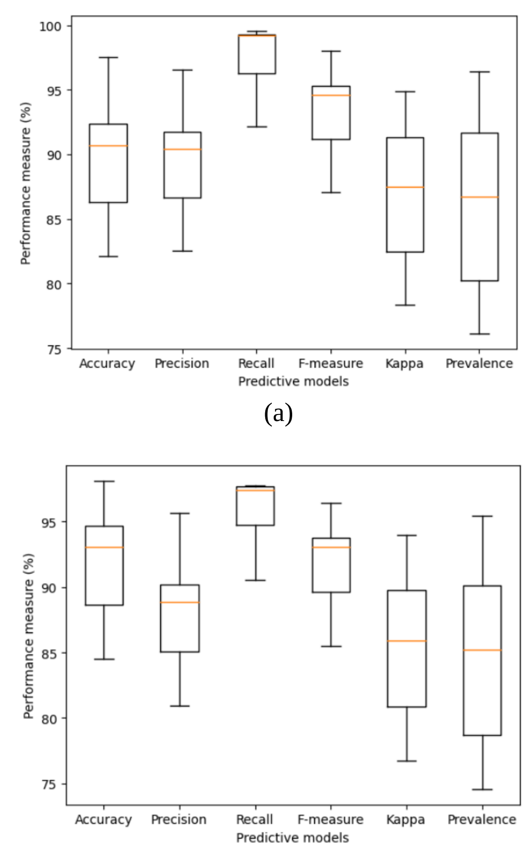
Predictive models	Performance measure (%)					
	Accuracy	**Precision**	**Recall**	**F-measure**	**Kappa**	**Prevalence**
RF	83.309	81.738	91.360	86.282	77.542	75.350
k-NN	85.677	84.106	93.728	88.657	79.910	77.718
DT	88.045	86.474	96.096	91.031	82.278	80.086
LR	90.413	88.842	98.464	93.406	84.646	82.454
RF+GMA-NN	93.534	90.453	98.455	94.284	88.781	90.244
k-NN+GMA-NN	93.335	91.669	98.533	94.977	90.251	89.477
DT+GMA-NN	93.543	90.704	98.361	94.377	91.584	92.877
LR+GMA-NN	97.846	96.138	98.985	97.255	94.442	95.923

5.4 Comparative investigation of predictive models

Table 8 shows the comparative investigation of predictive models for employability prediction. From the table, we depicts that the maximum accuracy is achieved by LR+GMA-NN model which is 14.857%, 12.437%, 10.017%, 7.597%, 4.407%, 4.61% and 4.398% higher than the RF, k-NN, DT, LR, RF+GMA-NN, k-NN+GMA-NN and DT+GMA-NN, respectively. The maximum precision is achieved by LR+GMA-NN model which is 14.978%, 12.515%, 10.052%, 7.589%, 5.913%, 4.649% and 5.652% higher than the RF, k-NN, DT, LR, RF+GMA-NN, k-NN+GMA-NN and DT+GMA-NN models, respectively. The maximum Recall is achieved by LR+GMA-NN model which is 7.703%, 5.311%, 2.919%, 0.526%, 0.536%, 0.457% and 0.63% higher than the RF, k-NN, DT, LR, RF+GMA-NN, k-NN+GMA-NN and DT+GMA-NN, respectively. The maximum F-measure is achieved by LR+GMA-NN model which is 11.283%, 8.841%, 6.4%, 3.958%, 3.055%, 2.342% and 2.959% higher than the RF, k-NN, DT, LR, RF+GMA-NN, k-NN+GMA-NN and DT+GMA-NN, respectively. The maximum kappa measure is achieved by LR+GMA-NN which is 17.895%, 15.387%, 12.88%, 10.373%, 5.994%, 4.438% and 3.026% higher than the RF, k-NN, DT, LR, RF+GMA-NN, k-NN+GMA-NN and DT+GMA-NN, respectively. The maximum Prevalence measure is achieved by LR+GMA-NN model which is 75.35%, 77.718%, 80.086%, 82.454%, 90.244%, 89.477%, 92.877% and 95.923% higher than RF, k-NN, DT, LR, RF+GMA-NN, k-NN+GMA-NN and DT+GMA-NN models, respectively. Fig. 4 shows a comprehensive results of the predictive models' effectiveness in addressing the challenges associated with both class-0 and class-1 employability scenarios, offering valuable insights for decision-making and model selection. Utilizing the outcomes of our prediction model, we have constructed a contingency matrix representing employability, as illustrated in Fig. 5.

5.5 Case study: "Educational institutions-India"

Background: Educational institutions in India follow various procedures especially during the placement period. This includes fielding students for industry internships/ externships, technical, communication and behavioral skills training, entrepreneurship training and standardized tests, GRE, TOEFL or GATE. They also organize faculty development programs and placement partnerships with



(a)

(b)

Fig. 4 Comparative analysis of predictive models for employability prediction with (a) class-0 (b) class-1

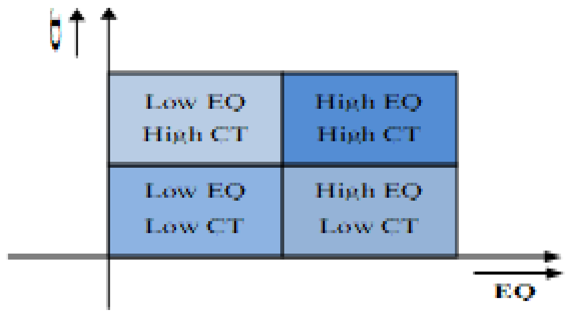


Fig. 5 Contingency matrix for the employability

corporate organizations. Through these activities, educational institutions aim to impart the necessary skills to students. Gaps in Educational institutions: India's educational environment presents unique challenges. The rapid growth of the IT industry has led to high demand for skilled professionals, especially in the field of computer science. Educational institutions are under pressure to produce graduates who are ready not only academically but also for industry. Despite their best efforts, educational institutions often struggle to accurately predict the employability of their graduates and match their skills to industry requirements. Solution for the gap: To address these challenges, the proposed solutions are tailored to the Indian educational environment. We understand the specific needs of the Indian IT industry and the unique skills required for computer science graduates. Our predictive model goes beyond academic qualifications and includes hybrid elements including emotional quotient (EQ) and computational thinking (CT). EQ is an important aspect of employability as it reflects a student's personal abilities and soft skills. In the dynamic Indian work environment, a strong EQ is very important. CT graduates possess problem-solving and algorithmic skills that are particularly important in the field of computer science. Integrating EQ and CT into employability prediction models ensures high relevance to the needs of the Indian labor market. Educational institutions can use our model to make informed decisions and provide targeted education to their students and graduates. This helps bridge the gap between academia and industry and ultimately increases the employability of graduates. In conclusion, our proposal is uniquely designed to address the specific challenges faced by Indian educational institutions. We provide data-driven solutions that address the diverse needs of the Indian IT sector and the skill sets required for computer science graduates. Using our model, organizations can take proactive steps to improve the employability of their students and prepare them for success in a competitive labor market. Summary: Finally, we concluded that our proposed solution is suitable for the Indian academic environment and provides holistic approach to graduate employability. It provides organizations with the tools they need to develop well-rounded professionals who can succeed in IT and other industries. In essence, our proposal is a proactive step towards a brighter future for educational institutions and their graduates.

6. Conclusion

We have introduced a comprehensive framework to explore the connection between EQ and CT and their influence the employability of computer science graduates. Our approach incorporates EFA and CFA to validate the key employability, specifically EQ and CT. For employability prediction, we employ an ensemble models, including random forest, decision tree, k-nearest neighbor, and logistic regression. The most effective model identified in this phase is then employed in the subsequent stage. Here, a generative multi-in-one artificial neural network (GMA-NN) is used to generate the employability prediction. To appraise the presentation and efficiency of our model, we construct a contingency matrix for employability using the identified design factors. Notably, our LR+GMA-NN model achieves a remarkable maximum accuracy of 97.846%. The result surpasses the accuracy of other models by significant margins, with improvements of 14.857%, 12.437%, 10.017%, 7.597%, 4.407%, 4.61%, and 4.398% compared to RF, k-NN, DT, LR, RF+GMA-NN, k-NN+GMA-NN, and DT+GMA-NN, respectively. The result reflects that small change in the proposed model over the existing models. There is room for future improvement if additional factors affecting employment are identified. The goal of this test is to minimize false positives and maximize detection rate. Additionally, we plan to implement an efficient verification model to increase the accuracy of employability predictions.

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