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A Multilayer Prediction Approach for the Student Cognitive Skills Measurement

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ABSTRACT Every year, a large volume of information about students' performance is processed in schools, colleges, and higher studies institutes. This information statistically associates students' performance with their study schedule and family-related characteristics. Recent methods have significantly contributed to student's cognitive skills (CSs) prediction area of research, but they are insufficient to address the challenges created by Study-Related Characteristics (SRC) of a student. Therefore, in the current attempt, we present a multilayer CS measurement method that uses SRC for student's skills prediction. The contributions of the proposed method are threefold. First, during quantization, a multilayer model is initiated by splitting SRC into five factors, and a specific range is assigned to each factor (timing schedules of studying, outing, traveling to school, and free timing as well as parent's relationships). Second, the range of CS (0–20) is divided into 21 periodic intervals (with a period of 1). The component-wise division of SRC and CS is to ensure prediction accuracy that makes the method more testable and maintainable. Third, it simulates the nonlinear relationship between CS intervals and SRC layers using Gauss–Newton method. Finally, we achieved six mathematical models for the SRC. During the experiment, the proposed method is tested on the students' performance data sets. The results reveal that the current approach outperformed the existing CS measurement techniques because we achieved a significant precision (0.979), recall (0.912), F1 score (0.9249), and accuracy measure (0.937) values. In the end, this paper is concluded by comparing the proposed method with competitive student's skills prediction approaches.

INDEX TERMS Cognitive skills prediction, study-related characteristics model, student's skills quantization, student's skills simulation.

I. INTRODUCTION

Cognitive Skills (CS) prediction is essential to track the time-varying knowledge state of a student. Discovering knowledge state can enable school management to pinpoint the weaknesses of students in their performance and help them in recovering these deficiencies, e.g., recommend a psychologist, the student need their parents to reschedule study related timing. The prediction of the student's CS depends on different factors, e.g., study schedule, family-related characteristics, and problems due to frustration [1]. Literature has related CS with these students' characteristics [2]–[5]. There are prior methods that predict students' CS using grades and study-related information of the students [6]–[8]. Lindsey *et al.* [9] presented an approach that predicts students' skills by using their performance data (exercise solution can be correct or incorrect). According to this particular technique, the skills of the student increases monotonically with the correct answer to an exercise. Additionally, the CS of the student has no specific limit because it increases monotonically with the correct solutions of the student.

These methods provided significant contributions in the field of student's CS prediction; however, such techniques are insufficient for the measurement of CS in different circumstances, e.g., students' prediction of primary, secondary and higher studies institutions. To accurately modulate student's CS, the recent methods have limited capabilities to address quantization, modulation, and simulation of Study-Related

Characteristics (SRC). The SRC consists of travel schedule, study schedule, outing schedule, free timing and the relationship between parents. Consequently, ignoring the relationship between SRC and CS can compromise the accuracy of the student prediction method. Focusing SRC can add two essential featured areas to the prediction model; (1) identify problems in daily life activities, and study related timing schedule of the student, and (2) discover issues created by the bad relationship between student's parents. Thus, the recent methods are incapable of addressing new challenges in CS measurement, i.e., (1) quantize Study-Related characteristics (SRC) and skills of the student, (2) design a multilayer model of SRC for the simulation of the relationship between CS and SRC, and (3) initiate a mathematical solution for the simulation of the nonlinear relationship between CS and SRC layer model. Therefore, through accurate quantization and modulation of SRC and CS, the method can efficiently predict CS of the students. The technique can track the knowledge state (weaknesses and strengths) of a student. The student's study schedule and family-related environment affect the particular level of CS [10]–[15]. Thus, the identified weaknesses can be overcome through a proper guideline provided by the psychologist or a tutor. The in-depth investigation has enabled us to the simulation of the relationship between CS and SRC for the student's skills prediction. Such simulations can increase the accuracy of the prediction method. Therefore, in the current attempt, we have proposed a method that quantizes CS and SRC. It iteratively modulates the relationship between SRC and CS.

During quantization, the proposed method splits SRC into five factors, and then specific ranges are assigned to these factors, i.e., 1) travel timing schedule between school and home (range is 1 to 5), 2) study schedule (range is 1 to 4), 3) outing schedule (range is 1 to 5), 4) free timing (range is 1 to 5), and 5) parent's relationship (range is 1 to 5. 1 is referred to as bad relationship while 5 denotes the excellent relationship). Furthermore, dividing SRC into five factors are referred to as the multilayer model of the method. The technique has split the range of CS (0 to 20) into 21 periodic intervals (with a period of 1). This particular quantization of CS increases the accuracy and preciseness of the student's skills prediction because it has enabled us to build a prediction technique that can calculate component wise (CS periodic outcomes) CS values. Such CS range makes the proposed method more maintainable and testable. Each factor of SRC has a nonlinear relationship with CS intervals. The proposed method uses the Gauss-Newton Algorithm (GNA) to simulate the nonlinear relationships between SRC and CS. GNA iteratively simulates the correlation between CS and each factor of SRC. Eventually, we have achieved five model equations for travel timing, study timing schedule, outing schedule and family environment between student's parents while two model equations for free timing schedule. Therefore, the main contributions of the proposed technique are threefold.

- The proposed method has quantized students' study-related characteristics and CS.
- To evaluate the expected value of a student's CS, we have developed a five-layered (multilayer) model of SRC. Each layer of SRC has a nonlinear relationship with the periodic intervals of student's CS.
- To simulate the nonlinear relationship between CS and SRC, we have achieved six model equations for the SRC multilayer model.

During the experiment, the proposed method was tested on the students' performance datasets [6], [16]. The results illustrated that the proposed method achieved a significant prediction accuracy. Besides, the accuracy of each model of the proposed method is evaluated separately. The results of these models showed that the proposed method outperformed the existing CS measurement techniques. Thus, the current approach successfully simulated the relationship between CS and SRC because precision, recall, F1 score and accuracy measures represent significant performance values. Finally, the current method is compared with the competitive CS prediction approaches that concluded the current work.

Moreover, section II presents the related work. The quantization is explained in section III while the simulation is discussed in section IV followed by results, comparison, and discussion in section V. The paper is concluded in section VI.

II. RELATED WORK

The extensive study of the human cognitive system shows that the cognition uses the information to guide and initiate the expected actions of a person [17]–[24]. Such information is obtained during the interaction of an individual with the external world. More specifically, the cognitive system is an information processing technique that quickly affects the studies and family routine activities of the students. This cognitive structure is influenced by study schedule and family-related characteristics of a student. Here the most important feature is the identical structure of the information processing system of a student that can predict the expected performance of a student. Therefore, the cognitive structure and the characteristics as SRC can be used for the development of a skills prediction algorithm (cognitive architecture).

Xu *et al.* [8] focused on accurate prediction of students' skills for the qualification of degree requirements. They have addressed three challenges as ; (1) difference in student background, (2) the selected courses may not be equally informative for prediction, (3) the progress information of the student. Their proposed technique has successfully addressed these challenges by multiple base predictors and data-driven approach (that based on matrix factorization). This particular technique has mainly focused on the evolving states of the student's performance as well as course relevance. This method has many deficiencies to achieve accurate quantization of students' skills as well as quantization of those factors which can positively or negatively affect these skills, e.g., studying, outing and the traveling schedules between school and home as well as the relationship between a student's parents. On the other hand, our current attempt is to accurately quantize such factors and then modulate it as the layers of the umbrella. Therefore, we can check the expected value of CS under the influence of the proposed umbrella.

Kidziński *et al.* [25] focused on the student's skills prediction algorithm analysis. The main challenge in students' skills prediction area of research is the selection of student's performance related factors. The second important approach is to accurately quantize these factors while the third challenge is to define an iterative and sub-iterative method for the measurement of students' CS. During iterative system development, we need a method (e.g., Gauss-Newton algorithm, Bayesian inference, and Recurrent Neural Network, etc.) that can calculate and simulate the relationship between SRC and students' CS [26]–[30]. Bergin [31] has Ph.D. thesis on the development of techniques for the prediction of CS of a student. It has two classes as outcomes of CS (class one=weak, or class two=strong skills). According to the selected challenges of the thesis, the author has significant contributions; however, this literature has a lack of accurate selection of range. It is also insufficient in quantization and collection of related factors to predict CS before student's performance (study schedules and family-related issues).

Pojon [32] investigated different machine learning technique as Naive Bayes, decision tree, and the regression analysis but this method is not able to predict student's performance that based on quantization and simulation. This work also has a lack of focus on the splitting of student's characteristics into different layers as well as modeling. They also have focused on feature engineering that mainly taken the features of the dataset. Furthermore, Iqbal *et al.* [33] used real-world data (collected in information technology university Lahore). They compared the collaborative filtering matrix factorization and restricted Boltzmann machine to predict the skills of the students that based on their grades. It has been elaborated in the literature that a student's performance is dependent on their study-related schedules. So, this method has limitations for the accurate measurement of CS during cognitive tasks (prediction based on SRC). Lillard *et al.* [34] proposed a method for the childhood development. It has limitations during evaluation of the study-related, and family-related characteristics. Therefore, it can compromise the efficiency of the student's prediction method. The basic course as grammar and comprehension is essential for a good outcome in each subject, but SRC and its quantization increase the accuracy of the method.

Garbacz *et al.* [35] expressed that family environment and education play a crucial role in the improvement of student's skill. Therefore, working with CS measurement, we need psychological finding to identify the relationship between CS and SRC. The family environment and parents' relationship can overcome by family structure recommendation (a psychologist can suggest that). Ohye *et al.* [36] focused on three generation family structure to address the challenges and problems in a family system. Fosco *et al.* [37] also concentrated on the family-related issues that are addressed by family checkup. Therefore, the most significant attribute of SRC is the family relationship of a student. Thus, the primary need is to select the correct family and study related characteristics of the students and then correctly quantize it to modulate the relationship between CS and SRC.

The proposed method is scalable for CS measurement during the primary, secondary as well as higher educational institutions. In literature, we have no in-depth and sufficiently scalable solution for measuring and tracking student's CS that need specific attention from a psychologist or a teacher. Therefore, addressing the current challenges of the proposed method can enable us to precisely and accurately predict student's CS. Käser *et al.* [38] attempted to analyze and predict student's performance that based on mathematics course results. This particular dataset is obtained from a computer-based training system. As according to the proposed challenges, this method has different deficiencies, e.g., static in factor selection (only performance of mathematics) as well as no proper quantization of student's CS. Furthermore, it has no iterative system that enables us to refine the relationship between CS and student characteristics, e.g., RNN remembers the previous outcome of the method [39]–[44]. Therefore, the previous outcome and the values of the SRC can bring together to predict the outcome of a student's performance. Thus, we need to develop an iterative system that can automatically refine the relationship between SRC and CS outcome.

Furthermore, Livieris *et al.* [45] discussed the implementation of a tool in student's CS prediction scenario. This particular tool uses a neural network classifier to predict the performance of a student in a mathematics course. In student's CS measurement circumstances (during cognitive tasks), focusing only on tools can compromise the novelty of the method because an accurate and precise prediction system need proper quantization and modulation of the problem. We can use these tools (RNN, NN, and Bayesian Inference, etc.) in a different node of our proposed model because the most significant innovation is to define a technique that can iteratively address the challenges of the student's CS prediction. Furthermore, the deficiencies and weakness in a student's CS are overcome through a psychologist or a tutor. For the improvement of student's skills, the role of a teacher or a psychologist is essential.

Rovira *et al.* [46] proposed a data-driven approach to measure the relationship between the academic information and their characteristics. They mainly focused on the grades and personalized recommendation of the specific courses. However, only analyzing the well-known machine learning technique decreases the accuracy of the prediction because student's skills simulation need a proper focus on the quantization and iterative modulation of the factors (SRC and CS). Furthermore, accurate quantization and iterative design of prediction techniques are essential because the relationship between CS and student's characteristics is nonlinear. In addition, Liu *et al.* [47] demonstrated a collaborative learning approach that based on a cognitive model. This work mainly focused on the prediction and improvement of student's CS. The teamwork and facilitating environment of the student

TABLE 1. Quantization of CS outcome.

Continuous form of CS	Discrete form of CS	Partitioning of CS	Range Assignment	Range Assignment
0 to 0.5	0	Low CS outcome	0 to 5	P1
0.6 to 1.5	1	Low CS outcome	0 to 5	P1
1.6 to 2.5	2	Low CS outcome	0 to 5	P1
2.6 to 3.5	3	Low CS outcome	0 to 5	P1
3.6 to 4.5	4	Low CS outcome	0 to 5	P1
4.6 to 5.5	5	Low CS outcome	0 to 5	P1
5.6 to 6.5	6	Average CS outcome	6 to 10	P2
6.6 to 7.5	7	Average CS outcome	6 to 10	P2
7.6 to 8.5	8	Average CS outcome	6 to 10	P2
8.6 to 9.5	9	Average CS outcome	6 to 10	P2
9.6 to 10.5	10	Average CS outcome	6 to 10	P2
10.6 to 11.5	11	Good CS outcome	11 to 15	P3
11.6 to 12.5	12	Good CS outcome	11 to 15	P3
12.6 to 13.5	13	Good CS outcome	11 to 15	P3
13.6 to 14.5	14	Good CS outcome	11 to 15	P3
14.6 to 15.5	15	Good CS outcome	11 to 15	P3
15.6 to 16.5	16	Excellent CS outcome	16 to 20	P4
16.6 to 17.5	17	Excellent CS outcome	16 to 20	P4
17.6 to 18.5	18	Excellent CS outcome	16 to 20	P4
18.6 to 19.5	19	Excellent CS outcome	16 to 20	P4
19.6 to 20	20	Excellent CS outcome	16 to 20	P4

can enhance the particular CS level. These methods provided meaningful and significant contributions to the student's CS measurement approach; however, such methods are insufficient to address the specific challenges of the current attempt. Therefore, these limitations convinced us to develop a new technique for the quantization and iterative modulation of a students' CS as well as SRC.

III. QUANTIZATION

This section describes the particular quantization and iterative modulation of SRC and CS of a student. Firstly, the method has split the range of student's CS (0 to 20) into 21 periodic intervals (with a period of 1). Resultantly, we have achieved a component-wise quantization of student's skills that has ensured a significant prediction accuracy and precision. Furthermore, to overcome the high nonlinearity of CS and SRC, the technique organizes the outcome of CS into four partitions. Every partition consists of five outcomes of CS which is given below.

- The range of first Partition (P1), the second partition (P2) and third partition (P3) are 0 to 5, 6 to 10 and 11 to 15 respectively. The particular range of fourth partition (P3) is from 16 to 20.

Furthermore, the detail descriptions are given in Table (1). These partitions are referred to as Low CS (P1), Average CS (P2), Good CS (P3) and Excellent CS (P4) outcome partitions. The lower and upper bounds of the proposed prediction models are 0 and 20 respectively. Moreover, the calculations of the posterior probabilities of CS outcomes are beyond the scope of this study. On the other hand, the critical section of the current study is to quantize and modulate SRC to achieve a solution for the particular challenges of the method. During this process, the characteristics of SRC are split into five layers as (1) travel schedule, (2) study schedule, (3) outing schedule, (4) free timing and (5) the environment of the home of a student which is also referred to as parent's relationships. Thus, a specific range is assigned to each layer which created a five-layered model of SRC. The primary goal of splitting SRC into multiple layers is to efficiently modulate and simulate the nonlinear relationship between CS intervals and SRC of a student. Furthermore, splitting SRC into multiple layers is to ensure the accuracy and preciseness of the student's skills prediction method. The five-layered model can easily be escalated by adding other necessary characteristics of a student. The first layer of the model is referred to as the travel schedule. This layer manifests the round trip timing between the student's school and home. It shows a particular time in which a student can reach and come back from school. Fig. (1) shows the quantization details and the specific ranges of the five layers of SRC.

The study time reveals that how many hours a student studies (irrespective of schooling time) while the outing time represents the refreshment schedule (in hours) of a student. Free time shows a student's timing schedule for other activities (except for sleeping and the above-defined schedules). Finally, the family environment represents the relationship between the students' parents. It shows the understanding level between the parents of a student. This particular parent's relationship has a range from 1 (bad relationship) to 5 (excellent relationship). Thus, we have obtained a five-layered model of SRC. Resultantly, the proposed method has assigned ranges (from 1 to 5) to four partitions (travel, outing, free timing and family relationship). On the other hand, a separate range (from 1 to 4) has assigned to the study schedule of a student. In addition, Fig. (1) shows a detailed framework of the proposed method. This particular framework demonstrates the quantization steps as well as the iterative designing of SRC five-layered model. Fig. (1) also shows the simulation design of the proposed method.

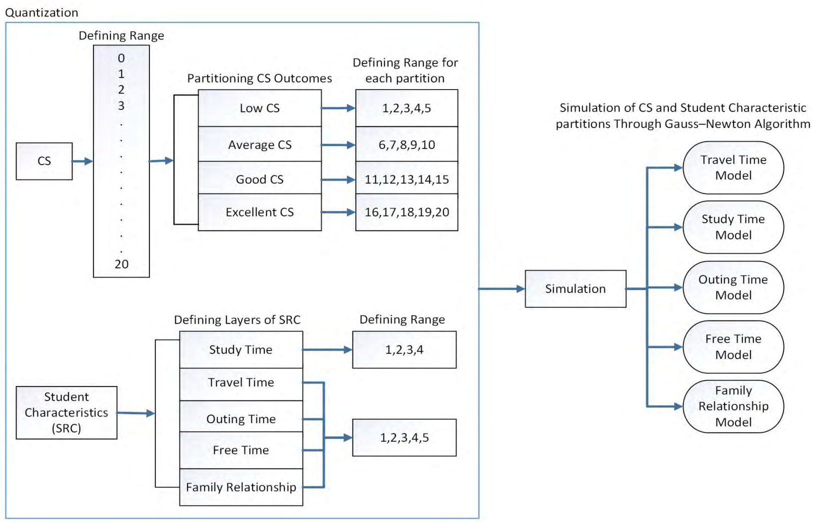

FIGURE 1. Framework of the proposed method (SRC and CS quantization, designing a multilayer model of SRC and then defining particular steps of CS simulation)

During quantization, we have two main categories as CS quantization and student's characteristics (SRC) quantization. The CS category has three further sections as defining a range for CS, partitioning this particular range and then distributing the outcomes of CS between these partitions. On the other hand, student characteristics have two sections which are referred to as partitioning and the development of ranges. In the partition section, the student's characteristics are divided into the five-layered model which are explained earlier. In the development of ranges section, the technique defines specific ranges for each layer of a student's SRC. In simulations, the method uses the Gauss-Newton Algorithm (GNA) for the parameter estimations. The detailed explanation of the simulation of the relationship between CS and student's characteristics are given in the following simulation section of the current study.

IV. SIMULATION

The relationships between CS and student multilayer model of SRC are highly nonlinear because many factors continuously affect the statistical association between these human factors. To overcome the problems created by such high nonlinearity are very challenging. Thus, the proposed method has organized the CS outcomes (21 outcomes) into four partitions. Such partitioning is to ensure efficient control of the proposed technique on high nonlinearity issues. Each partition of the CS consists of five outcomes of CS which are also shown in Table (1) (P1 to P4, each partition range is defined). Now the most critical task is to choose a machine learning technique for the particular parameters estimations between CS and SRC model (five-layered model). Thus, the proposed method uses the nonlinear least squares technique for the parameter estimations and simulations of the relationship between CS-partitions groups and the layers of the SRC of a student. Therefore, we use the Gauss-Newton Algorithm (GNA) for the particular parameters estimations that help in the simulation of the nonlinear relationship between CS and SRC. The fundamental reason behind the selection of GNA technique is to simulate the highly nonlinear least square problem efficiently. Besides, GNA is quite relevant for the solution of the problem description of our method. To iteratively re-estimate the unknown parameters of the model of SRC, GNA plays an essential role (comparatively) by simulating the nonlinear relationship between CS and student's characteristics. Working with the nonlinear relationship between CS and SRC is very challenging for other techniques (Bayesian Inference, Recurrent Neural Networks); therefore, by Taylor series, the GNA has efficiently estimated the unknown parameters of the proposed multilayer model. Therefore, GNA is embedded in the proposed method for parameters estimations between CS partitions and the model of SRC.

During simulation of the relationship between CS partitions and SRC, the method tries to fit a mathematical model to the data. Therefore, the student's characteristics play a role of an umbrella while their partitions are referred to as layers of the umbrella. The proposed method evaluates each partition of CS outcome under the influence of each layer of the student's SRC model. Thus, our method simulates the nonlinear correlation between each partition of CS outcomes and SRC ($cs_i = f(SRC, \theta) + \epsilon$) of a student using the nonlinear least square technique. The mathematical models for the simulation of the correlation between CS and student's characteristics are nonlinear in parameters. Therefore, the proposed method will transform the nonlinear model into the locally linear model. So, we have the initial model as follow.

$$cs_i = f(SRC^{(i)}, \theta) + \epsilon_i \tag{1}$$

In Eq. (1), the error $\epsilon_i = cs_i - (SRC^{(i)}, \theta)$ while cs_i represents CS outcomes' partitions ($i = 1$ to 4), SRC shows the partitions of the student study-characteristics as well as family-related problem (SRC). Furthermore, we minimize the error with respect to θ ($\theta^{Min}\{\sum_{i=1}^{N}\epsilon_i\}$). To initiate the iteration, the method need the initial guess for the parameters θ. Thus, lets say $\bar{\theta}$ = initial guess solution. Now, to transform the nonlinear parameter model to linear model, we use Taylor series. So, we obtain the following model.

$$cs_i = f(Student_{char}, \bar{\theta}) + (\frac{\partial f}{\partial \theta_1})_{\theta=\bar{\theta}} \triangle\theta_1 + \ldots + (\frac{\partial f}{\partial \theta_m})_{\theta=\bar{\theta}} \triangle\theta_m + \epsilon \tag{2}$$

Eq. (2) shows Taylor series with parameters (θ and $\bar{\theta}$) during simulation of the method. Now it is linear in the parameter model.

A. TRAINING SETS

The proposed method has initiated the simulation of the relationship between CS-partitions and the model of SRC using two datasets [6], [16]. The public dataset contains information about the student's characteristics and grades (G1, G2, G3). Therefore, during the proposed method simulation, G3 is referred to as CS-outcomes that has a specific range (0 to 20). The method simulates the statistical associations between SRC and CS (G3) while ignoring the other characteristics of the student. The data is highly nonlinear because the values of G3 have a statistical association with many other factors of the student. We divide the dataset into two sets: (1) the training set (70%) and (2) validation set (30%). Furthermore, to efficiently train the proposed method, we obtained another dataset that was collected during psychological experiments for the simulation of the relationship between CS and Basic Human Factors. In this dataset, the target attribute G3 (CS) has a strong correlation with other student characteristics and family-related attributes. Appendix A shows a sample from the psychological experiment based dataset. The first column of the table illustrates the related attributes of the dataset while the rest of the columns manifest the values of these particular attributes. In addition, this dataset is also divided into training and validation sets (training set is (70%) and (2) validation set is (30%)). In the simulation section, the training sets are used for parameters estimations and mathematical models building while the validation sets are used in the experiment section to test the accuracy and preciseness of the proposed method. Resultantly, we achieved a model of equations for every layer of the multilayer model of SRC. These model of equations are in the form of functions where each layer applied a specific action on CS partitions. The first simulated model of the relationship between CS-partitions and SRC model is referred to as travel schedule which is given by the following equation.

$$cs(tt) = ((\theta + \gamma) - (\alpha + tt)) + \cos(\omega) \tag{3}$$

Eq. (3) represents a model equation for the simulation of the statistical association between CS and travel time (tt). During the simulation process, the proposed method achieved four estimated parameters as $\theta = 3$, $\gamma = 11$, $\alpha = 2$ and $\omega = 1.3$ that are referred to as parameters of the model. The statistical analysis shows that an increase in travel time has a negative impact on CS of a student. Therefore, the achieved simulation model successfully modeled this particular relationship. The prediction of this model focuses on the relationship between CS-partitions and the student's SRC multi-layered model because the statistical association between CS and SRC is highly nonlinear. In addition, the simulation of a single CS-outcome and SRC model is beyond the scope of the current attempt. Furthermore, the proposed method achieved a mathematical model for the second layer of the SRC which is referred to as a study schedule of a student. Thus, the simulated statistical association between CS and the student's study schedule is given by the following equation.

$$cs(st) = (\alpha + \gamma) + \left\{\frac{\theta + \omega}{st}\right\} \tag{4}$$

In Eq. (4), st represents the study time of a student that has a range from 1 to 4 hours. The proposed method achieved a successful estimation for four unknown variables as $\theta = 3.41$, $\gamma = 3.9$, $\alpha = 2.3$ and $\omega = 2.369$ which are known as model parameters. This particular layer of SRC successfully achieved the goal of simulation of the relationship between CS-partitions and study schedule by adding the estimated parameters to Eq. (4). Furthermore, the method simulated the relationship between CS-partitions and student characteristic SRC layer as family relationship. A range (from 1 to 5 while 1 = worse and 5=very good) describes the quality of family relationships. The statistical analysis shows that CS is increasing with increase in understanding between a student's parents. Therefore, the obtained simulation model is given by the following equation.

$$cs(fr) = \sqrt{(fr \times \alpha)} + (fr + \theta) \times \omega \tag{5}$$

In Eq. (5), the variable fr represents the quality of the relationship between the independent variables (student's parent's relationship). The proposed method has simulated the nonlinear relationship between CS-partitions and the third layer (parent's relationship) of SRC by achieving the estimated parameters as $\alpha = 2, \theta = 1.5$, and $\omega = 2$. This layer of SRC obtained three parameters for simulations. Furthermore, the fourth layer of the SRC is referred to as outing schedule of a student (outing with friends: 1 is very low while five is very high). The particular data analysis shows that outing schedule has a positive relationship with CS because student's skills increase with an increase in outing time. The proposed method has developed a new model for the outing schedule layer of SRC which is given by the following equation.

$$cs(gout) = \frac{(gout \times (\theta + \omega))}{\sqrt{\alpha}} - gout \tag{6}$$

In Eq. (6), the variable for outing schedule is represented by $gout$. Furthermore, the parameters that contributed to the simulation are $\alpha = 3.8, \theta = 4.8$, and $\omega = 4.5$. These particular parameters are estimated to finalize the mathematical model for the simulation of the nonlinear relationship between CS-partitions and outing schedule layer of SRC. Moreover, the last layer of SRC multi-layered model is called as free timing schedule (or no activity schedule) of a student. This factor illustrates that a student can have free time (free time after school: 1 is referred to as very low while five is very high) regardless of the time of schooling, outing, traveling and study time. According to statistical analysis, free timing is divided into two groups with a domain from 1 to 3 hours and from 4 to 5 hours respectively. The purpose of division is to achieve accurate simulation model because the first group has a positive relationship while the second group has a negative relationship with CS of a student. Firstly, the simulation of the first group of free-timing schedule is achieved which is given by the following equation.

$$cs(F_{time1}) = (\alpha + \theta) + (F_{time1} \times \omega) + \sin(\gamma) \tag{7}$$

In Eq. (7), the free-timing of the first group is shown by F_{time1} while the estimated parameters are given by α, θ, γ and ω where $\alpha = 2.7, \theta = 2.5, \gamma = 2.4$ and $\omega = 3.2$. This particular four estimated parameters successfully simulated the nonlinear statistical correlations between CS-partitions and the first group of free-timing of the SRC model. Moreover, the proposed method has achieved the simulation model of the second group of the free-timing layer of SRC. Thus, the second group free-timing layer is given by the following equation.

$$cs(F_{time2}) = (\alpha + \theta) + \left\{ \frac{\omega - F_{time2}}{\sqrt{\gamma}} \right\} - F_{time2} \tag{8}$$

In Eq. (8), F_{time2} represents the second group of the free-timing layer of SRC while the four parameters are estimated to achieve accurate simulation results. These particular parameters are $\alpha = 6.9, \theta = 7.4, \gamma = 4$ and $\omega = 8$ which have efficiently simulated the nonlinear relationship between the four particular partitions of CS and the second group of the free-timing layer.

B. QUALITATIVE ANALYSIS

This section describes the accuracy and preciseness of the proposed CS measurement method. During qualitative analysis, we have examined the proposed method by precision, recall, F1 score and accuracy measures.

1) VALIDATION SET

During the experiment, we have used validation sets to evaluate the accuracy of the model. As we discussed earlier that the datasets are divided into two sections [6], [16]. The validation sets section of the dataset is used to test the accuracy and preciseness of the method. Due to the nonlinear form of the data, the method has further split CS-outcomes into four groups (As discussed earlier). Therefore, the accuracy of each layer of the proposed multilayer model of SRC is evaluated separately. We have achieved a significant accuracy for every layer of the SRC which are explained below.

2) PREDICTION ACCURACY ANALYSIS

The prediction accuracy of the travel schedule layer of SRC is shown in Fig. (2). The dotted line graph illustrates the predicted values of the model. The predicted values can map to any partition of the CS outcomes. Four parameters are contributing in this model which are shown by α, θ, γ, and ω. By the estimated parameters, this layer successfully simulated the nonlinear relationship between CS and the travel schedule of the student. The relationship between travel schedule and CS is negative because CS is continuously decreasing by an increase in the travel timing. The proposed mathematical model for travel schedule successfully achieved the simulation goal of the method.

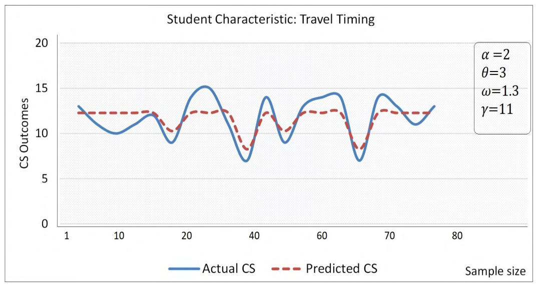

FIGURE 2. Manifests the predictions result of the travel timing model. Travel time shows the total time of the trip between home and school of a student.

To further evaluate the prediction accuracy, we have shown the particular partitions of CS outcomes as P1 (0 to 5), P2 (6 to 10), P3 (11 to 15), and P4 (16 to 20). This representation is to ensure the accuracy and to calculate the precision, recall and F1 scores of each layer of the proposed multilayer SCR model. The particular F1 is a good metric when the prediction of the model is built on an imbalance data. Therefore, our metric contains true positive P1 to P4 (TP1 to TP4) and false positive P1 to P4 (FP1 to FP4) as well as true negative (TN1 to TN4) and false negative (FN1 to FN4). Furthermore, the accuracy of the model is achieved by the following equation.

$$Accuracy = \frac{\sum_{i=1}^{4}(TP_i)}{\sum_{i=1}^{4}(TP_i + FP_i + TN_i + FN_i)} \tag{9}$$

Eq. (9) represents the model for the calculation of the accuracy of the proposed model of SRC where $i = 1$ to 4. TP represents true positive, FP shows false positive, TN represents true negative while FN manifests false negative. The list of the accuracy measures of the method are given in Table (2). During the experiment, we have obtained a good and satisfactory

TABLE 2. Qualitative measures.

Student Characteristic Model	CS Partitions	Precision	Recall	F1 Score	Accuracy
Travel time schedule	P1	0.919	0.892	0.9052	0.939
	P2	0.953	0.917	0.9346	0.967
	P3	0.928	0.909	0.9184	0.913
	P4	0.914	0.898	0.9059	0.927
Study time schedule	P1	0.936	0.911	0.9233	0.926
	P2	0.939	0.917	0.9278	0.945
	P3	0.928	0.921	0.9244	0.919
	P4	0.948	0.928	0.9378	0.932
Family Relationship	P1	0.899	0.889	0.8939	0.908
	P2	0.907	0.911	0.9089	0.896
	P3	0.929	0.907	0.9178	0.917
	P4	0.922	0.918	0.9199	0.921
Outing time schedule	P1	0.963	0.937	0.9498	0.953
	P2	0.976	0.938	0.9566	0.969
	P3	0.952	0.927	0.9393	0.951
	P4	0.964	0.937	0.9503	0.949
First group free time schedule	P1	0.897	0.899	0.8979	0.903
	P2	0.937	0.901	0.9186	0.928
	P3	0.941	0.918	0.9293	0.933
	P4	0.967	0.937	0.9151	0.949
Second group free time schedule	P1	0.971	0.901	0.9346	0.967
	P2	0.973	0.909	0.9399	0.968
	P3	0.969	0.871	0.9173	0.952
	P4	0.968	0.897	0.9311	0.961
Total		0.979	0.912	0.9249	0.937

level of the accuracies for P1 to P4 that are shown in Table (2). Furthermore, the precision measurement is obtained by the following model.

$$Precision = \frac{(TP_i)}{TP_i + \sum_{i=1}^{3}(FP_i)} \tag{10}$$

Eq. (10) is to measure the preciseness of the models. The parameters of Eq. (10) are explained earlier. For the travel schedule of the student, we have obtained a significant precision level (from P1 to P4) that is given in Table (2). Moreover, the recall of the predicted values is obtained by the following equation.

$$Recall = \frac{(TP_i)}{TP_i + \sum_{i=1}^{3}(FN_i)} \tag{11}$$

The Eq. (11) is to calculate the particular recall value of the SRC. We have achieved an excellent recall level for the travel schedule layer of the multilayer model of SRC (P1 to P4 CS outcomes partitions) that is illustrated in Table (2). Furthermore, the most critical measure is the F1 score because it calculates the preciseness of the model with imbalance predicted data. Thus, the F1 measure is given by the following equation.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{12}$$

Eq. (12) represents the model of the F1 score measure. By this measure, we have achieved an excellent value for the travel schedule of the method that is shown in Table (2).

The statistical association between CS and study schedule layer of the SRC multilayer model is successfully simulated. So, the Fig. (3) Illustrates the prediction results of the study schedule layer of the proposed method. It demonstrates that the prediction results and actual values of CS belong to the same partition of the CS outcomes. During model building, we estimated four parameters (α, θ, γ, and ω) that have helped us in the successful simulation of the study schedule. The further exploration of the prediction result (that how much its close to actual CS outcome) of the model is beyond the scope of the current study. Furthermore, the preciseness and accuracy of the model are obtained by accuracy measure, recall, precision and F1 score measures that are given in Table (2). These measures give us excellent outcomes for the particular four partitions of the CS outcomes (P1 to P4).

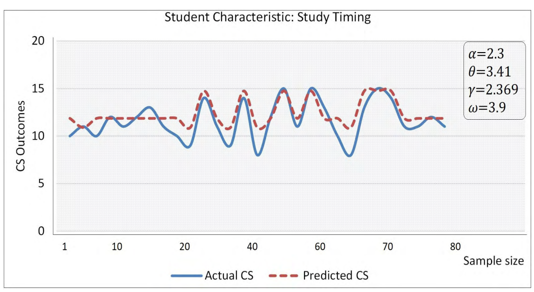

FIGURE 3. Shows the study timing model result of the SRC. The figure illustrates the values of the parameters.

The next mathematical model for the third layer of SRC multilayer model is referred to as a family environment of the student. Family environment means that how good is the relationship between the student's parents. The CS outcomes have a positive statistical association between family relationship and CS because CS is increased as with the increase in understanding between parents of the student. The simulation results are compared with actual CS outcomes that are shown in Fig. (4). The estimated parameters (α, θ, and ω.) efficiently contributed to the simulation of the model. The results manifest a good accuracy level of the prediction model because the actual and predicted values of the CS belongs to the same partitions (in each iteration). This model is further explored by the F1 score, precision, recall and accuracy measure that also show significant accuracy results. The outcomes of these measures are shown in Table (2).

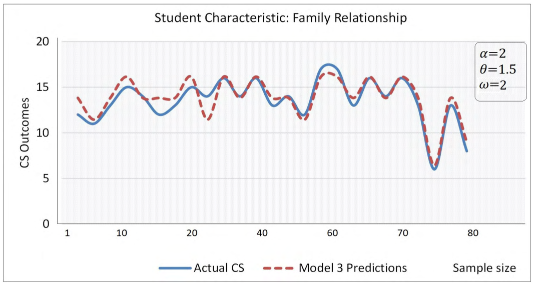

FIGURE 4. Reveals that the statistical association between CS and family relationship is simulated by the propose model.

The fourth layer of SRC multilayer model of a student is referred to as outing schedule. The proposed model simulates the nonlinear relationship between CS and outing schedule. In addition, the prediction results are shown in Fig. (5). The dotted line graph and actual values of the CS are mapping to the same partitions. The estimated parameters are α, θ, and ω. Furthermore, the measurement of the preciseness of the proposed model is obtained by accuracy measure, precision, recall and F1 score. These particular measures have shown excellent and satisfactory results for the family relationship layer of the proposed multilayer model of SRC. The results of these particular measures are given in Table (2).

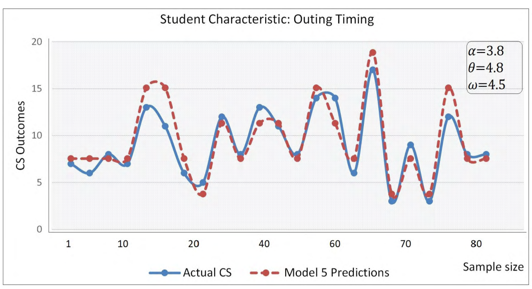

FIGURE 5. Illustrates the simulation result of outing time model of student characteristics. This shows the predicted and actual CS values where the predicted values are obtained by the propose model.

The fifth (last) layer of the SRC multilayer model is divided into two groups that are referred to as first group free-timing schedule (1 to 3 hours) and second group free-timing schedule (4 to 5 hours). An increase in the timing of the first group free time schedule has a positive relationship with CS outcomes because CS is increasing with an increase in the free-timing of the student. On the other hand, the particular second group of free-timing has a negative correlation with CS because of an increase in time (hours) negatively influence CS of a student. The results of the first group are shown in Fig. (6) which have four estimated parameters (α, θ, γ, and ω) while an independent variable. Moreover, the second group result is shown in Fig. (7) that also shows the same four parameters with different values. The technique has successfully simulated the relationship between CS and the two groups of free-timing schedule. The results have manifested that the accuracy of both the layers of SRC is satisfactory and significant because the predicted and actual values belong to the same partition of the CS outcomes. Furthermore, the precision, recall, accuracy and F1 score measures are used to calculate the fitness of the model for the particular problem of CS measurement of the student. These measures have shown that both the model (group 1 and 2) outperformed the existing methods because we obtained an impressive outcomes as the results of these measures. Moreover, the values of these measures are given in Table (2).

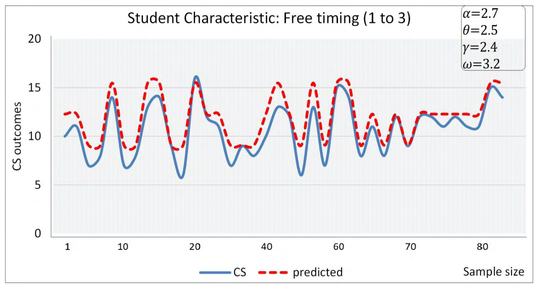

FIGURE 6. Shows the model of the first group of the student characteristic "free timing (1 to 3 hours)".

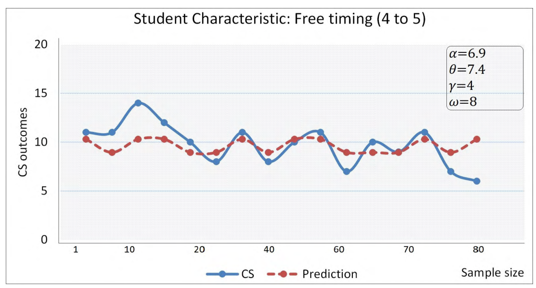

FIGURE 7. Shows the result of the second group of the free timing. The figure illustrates that the proposed model successfully simulated the statistical association between CS outcomes and student characteristic = free timing (4 to 5 hours)

3) PREDICTION ANALYSIS OF STUDY RELATED CHARACTERISTICS

This section represents the factor-wise prediction analysis of the proposed method. During this process, we have investigated prediction performance by increasing (stepwise) the values of input of the student's characteristics (SRC). By this process, we have achieved predictions of CS that are shown in Fig. (8) to (13). The prediction results manifest that we have successfully obtained our goal by simulating the relationship between CS and each layer of the SRC multilayer model. The simulation results of the travel schedule and CS are shown in Fig. (8). The prediction shows that CS is decreasing with an increase in the travel schedule (traveling time between school and home). This particular Fig. (8) manifests the highest value of CS outcome under the influence of 1 while the lowest value of CS under the influence of 5. Fig. (9) shows the prediction results of outing schedule model of the proposed method. The simulation results show that an increase in the outing schedule has a positive impact on student skills. Under the influence of 1 (as an outing schedule), we have the lowest value of CS while under the influence of 5 (as an outing schedule), we have a highest CS value for a student. Such results clearly illustrate that the nonlinear relationship between CS and outing schedule are successfully simulated.

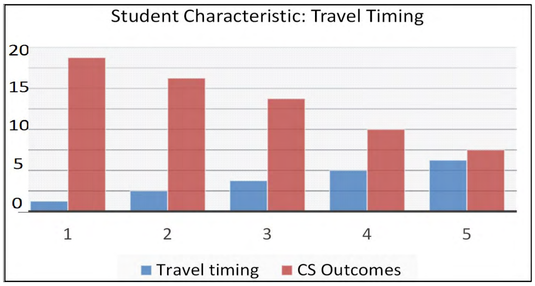

FIGURE 8. The values of student CS continuously decreasing with increase in travel timing schedule.

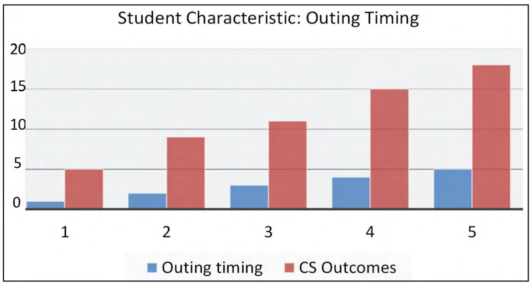

FIGURE 9. CS values of student is increasing with an increase in outing time schedule.

Fig. (10) demonstrates the results of family relationship model of the proposed method. The particular relationship between CS and family environment of the student is always very strong. The CS outcome of a student is always positively impacted by good family environment because the figure shows that the CS of a student increases with an increase in the values of the student's family relationship. The model has the lowest outcome with respect to 1 while it has the highest CS value with respect to 5. Fig. (11) represents the results of the study schedule. The simulation results show

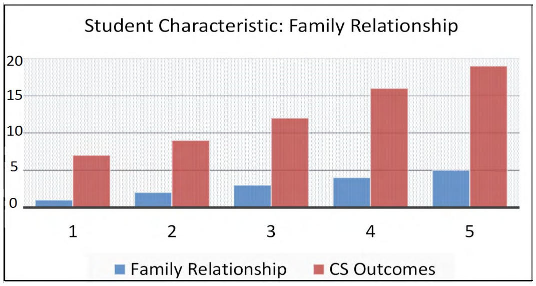

FIGURE 10. Represents the simulation results of family relationship. The CS value increases with the betterment in understanding between student parents.

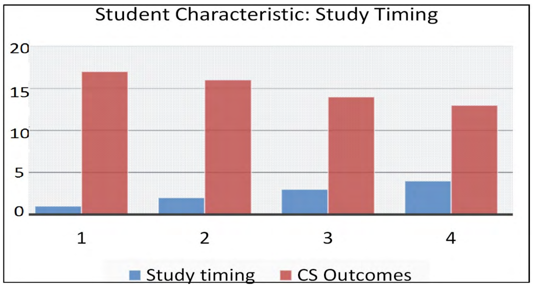

FIGURE 11. Simulation results show that CS is decreasing with increase in study time schedule.

that a student has the highest CS under the influence of 1 while it has the lowest skills under the influence of 4 (as study schedule). The next layer of the SRC multilayer model of the proposed method is free-timing schedule. According to the relationship between CS and free-timing schedule, we have divided free time into two groups (as discussed earlier in prediction accuracy analysis sub-section). The first group has a positive relationship with a student because CS is increasing with an increase in free time. As with 1-hour free-timing, we obtained the lowest values for CS while with 3 hours free-timing, we have achieved the highest values for student's CS. The second group has a negative relationship with student's skills because, with an increase in the free time, the student's skills are decreasing continuously (4 has the highest CS while 5 has the lowest CS). The Study-related Characteristics (SRC) of the student have five primary factors (timing schedules of studying, outing, traveling to school, and free timing as well as parent's relationships). To increase the efficiency and accuracy of the student's skills prediction, every factor of the SRC has considered as a separate layer which has produced better results (precision, F1 score, accuracy, and recall) as compared to the six-layered (or with more layers) model. Furthermore, to avoid uncertainty and ensure transparency, we have chosen the multi-layered (with five layers) model of SRC.

4) COMPARATIVE ANALYSIS

The comparison of the proposed technique is conducted with three competitive methods as Automatic Discovery of

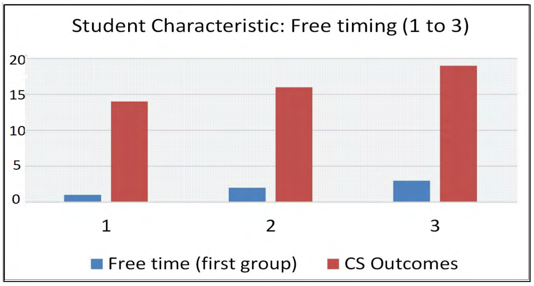

FIGURE 12. **Manifests the first group of free time while CS is increasing with an increase in free time schedule of a student.**

Cognitive Skills (ADCS) [9], Machine Learning Approach for Tracking and Predicting Student Performance (MLTPSP approach) [8], and Biologically Inspired Cognitive Skills Measurement Approach (BICSM approach) [6]. The ADCS has presented a technique that discovered the CS of a student by using student's performance datasets. The skills of the student have increased with the correct attempts of exercises because latent skills are attached to each exercise. Therefore, these latent skills increase the expected accuracy of the student. Furthermore, to attach (with expected prediction value) the skills identified by experts (e.g., teachers), the method has used a nonparametric Bayesian technique and weighted Chinese restaurant process to calculate the prior probability of the student's performance. Comparatively, our technique is novel and differ from ADCS. The most important feature of the proposed method is to extend the motivation of ADCS towards the discovery of the student's CS affected by their characteristics. The relationship between the student's parents and study-related schedules are quantized and modulated. Thus, the current method also extendable towards CS measurement during job interviews and written examinations. The ADCS has a lack of addressing those student's characteristics (SRC) that are beyond the school studies circumstances. Therefore, the proposed method is to quantize SRC and then construct a multi-layered model (multilayer SRC) to discover and simulate the nonlinear relationship between SRC and CS.

Developing such multilayer architecture increases the precision of the method because it makes the proposed method more testable and maintainable. The SRC can easily affect a student's CS because these are common characteristics of cognitive tasks. The second innovation is to quantize CS of a student. According to ADCS, the skills of a student have no specific limits (range) because it increases monotonically with correctly attempting exercises. Defining a particular range for CS is essential to categorize student skills into different categories, e.g., poor CS, Good CS or excellent CS. On the other hand, the proposed technique has adequately quantized CS and further split it into 21 periodic intervals. Defining such range help us in measuring the accuracy of the proposed prediction technique. Furthermore, splitting the range into periodic CS-outcomes ensure prediction accuracy because we have achieved the component-wise simulation model for each student. In addition, the proposed range of CS has enabled us to categorize CS intervals into four partitions (very low CS (0 to 5), average CS (6 to 10), good CS (11 to 15) and excellent CS outcomes (16 to 20)). Additionally, the proposed method has evaluated the relationship between each layer of the SRC model and CS intervals that has ensured the accuracy of the current CS prediction technique. Our method has achieved a component-wise simulation approach because the particular statistical association of each layer of SRC and CS interval is simulated separately. The component-wise simulation has enhanced the precision of the current method.

Furthermore, the proposed method is compared with another competitive method that is referred to as Machine Learning Approach for Tracking and Predicting Student Performance (MLTPSP approach) [8]. This approach has predicted student performance by addressing three challenges, e.g., (1) student is varying due to background and courses information, (2) Courses are equally informative or not, and (3) student's evolving progress should be added to the prediction model. This method is insufficient to achieve efficient quantization, design architecture for SRC and to simulate the correlation between each layer of SRC and CS intervals. This competitive method has a lack of precise quantization for a student's skills. Such quantization can help in the categorization of student's skills in a precise way. Furthermore, the particular competitive method has focused on the designing of the predictor (multiple based) and probabilistic matrix factorization while the proposed method has focused on enhancing prediction accuracy by designing a multilayer model of SRC and CS. The proposed method ensured accuracy by proposing a specific range for CS and further splitting it into 21 periodic intervals while the competitive method has a lack of such features which can address the challenges of the proposed method.

The proposed CS measurement technique is compared with another competitive method known as BICSM approach. This competitive method has proposed CS measurement algorithm that simulates the nonlinear relationship between CS and Basic Human Factors (BHF) (aging, infection, emotions, awareness, personality, education, and experience). This algorithm was split into three sub-algorithms, (1) estimate BHF factor values, (2) validate the estimated values of BHF, and (3) measure CS by using the estimated values of BHF. Furthermore, this method has also defined a continuous range for CS (0 to 10 on a Likert scale) with no explicit quantization. It has also proposed specific domains and ranges for BHF. Therefore, the nonlinear least square method was used to estimate the unknown parameters. Furthermore, it modulated the relationship between CS and BHF which resulted in CS measurement algorithm. The proposed technique is efficient and more detailed as compared to the BICM approach. Our technique has focused on a specific problem which has given us an important contribution to the field of CS measurement. The proposed technique can measure CS during studies of the students by targeting those student's characteristics that have a close relationship with CS. These characteristics are referred to as SRC which are explained earlier. Furthermore, BICSM approach is very ambiguous because it has too many BHF that is hard to achieve the goal of an in-depth factor wise quantization and simulation. Besides, our technique is new and accurate due to the following technical reasons.

- The current method proposed SRC and then developed a multilayer model for student's characteristics (SRC multilayer model).
- It assigned a range to CS of student and then divided it into periodic intervals. Such division successfully increased the accuracy of the method.
- It simulated the relationship between each layer of the SRC model and CS interval. This feature of the proposed approach efficiently enhanced the preciseness of the method.

Therefore, the proposed technique is efficient and accurate because it has defined different layers of SRC and then iteratively simulated the relationship between each layer and CS intervals. Our technique is dynamic as compared to BICSM approach because we need quantization for a new factor to be added to our model while BICSM approach is static in such situations. Furthermore, the proposed method is validated on the validation set (the dataset used for testing the accuracy of BICSM approach). During this process, every model of SRC layer is tested on the dataset. During this process, the proposed layers of SRC are tested as a two partition environment because the range of CS is from 0 to 10 in that particular dataset. The results show that the models of the proposed method have achieved significant accuracies as compared to BICSM approach. These particular results are given in Table (3). These results have manifested that we have achieved a significant accuracy on Mean Forecast Error (MFE), Mean Absolute Deviation (MAD) and Tracking Signal (TS) measures. Therefore, the proposed method has obtained more than 94% MFE for each layer of the method. It shows that our technique accuracy is more than 94% (because MFE error is less than 3%). Finally, we have obtained MAD and TS for each model which manifested that our technique is comparatively significant.

5) SCALABILITY ANALYSIS

The proposed method is dynamic because it can utilize other attributes of the students, e.g., study, family, and emotion (frustration). This method described an architecture that can be used in multifaceted environments, e.g., primary, secondary and higher studies institution as well as detection of student's skills during interviews and written examinations because frustration always negatively affect CS during such cognitive tasks. The student gets frustrated due to long drive or travel as well as because of multiple rejections from an interview. Ahmad *et al.* [6] have mainly focused on the data analysis while in the current attempt we have developed a dynamic architecture for the student's CS that can identify problems and weaknesses due to family and study related schedules. Such problems can be further overcome through proper check-up by a psychologist or a tutor. Furthermore, the multi-layered architecture of the SRC are extendable by adding more layers in the future; however, this work is beyond the scope of the current attempt. The recent methods are insufficient to obtain such scalability as the proposed method achieved.

V. DISCUSSION

The current attempt proposed a student's Cognitive skills (CS) prediction approach that based on their Study-Related Characteristics (SRC). The proposed method has addressed the following challenges.

- SRC can negatively or positively influence student's CS, and there is a strong nonlinear relationship between CS and SRC.
- To ensure a good prediction precision and accuracy, design a multilayer model that consists of SRC factors of a student.
- Simulate the nonlinear relationship between CS and SRC-based multilayer model by defining a mathematical method.

The recent methods are insufficient to address these particular challenges. Thus, the proposed method split SRC into five factors that created a five-layered model (also referred to as a multilayer model) of SRC. The multilayer model consists of travel-timing schedule between school and home, study schedule, outing schedule, free-timing, and a relationship between parents. Splitting SRC has enhanced the preciseness of the method by discovering the nonlinear relationship between each layer of SRC with CS. A Specific range is assigned to each layer of SRC. Besides, CS range (0 to 20) is divided into 21 periodic intervals with a period of 1. The division of CS and SRC is achieved to ensure precision and prediction accuracy. Furthermore, to accurately simulate the relationship between CS intervals and the model of SRC, the method used the Gauss-Newton Algorithm (GNA). GNA enabled us to simulate the relationship between CS and SRC. Therefore, the proposed method achieved six mathematical equations for the multilayer model of SRC (see Eq. (3) to Eq. (8)). During the experiment, the current method was tested on the students' performance datasets. The results of the experiment have shown that the proposed method achieved maximum accuracy on precision, recall, F1 score and accuracy measures (see Table (2) and Fig. (2) to Fig (13)).

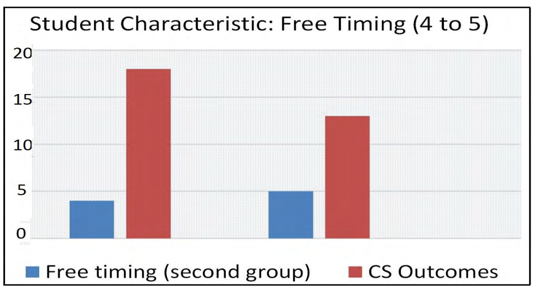

FIGURE 13. Shows the results of the second group of free time schedule. It reveals that CS is decreasing with increase in free time schedule.

TABLE 3. Accuracy comparison.

	Methods	MFE	MAD	TS
Recent Method	BICSM Approach	0.091(91%)	1.731	1.0
Proposed Models	Travel time schedule	0.098(98%)	1.711	-1.2
	Study time schedule	0.095(95%)	1.718	1.1
	Family Relationship	0.096(96%)	1.801	-1.4
	Outing time schedule	0.094(94%)	1.821	-1.3
	First group free time schedule	0.096(96%)	1.715	1.6
	Second group free time schedule	0.094(94%)	1.781	-1.9

TABLE 4. Psychological experiment based dataset sample.

sex	F	M	F	F	M	M	M	F	M	F	F
age	20	21	21	18	16	17	19	19	15	20	17
address	R	R	R	R	R	R	R	R	R	R	R
famsize	LE3	GT3	LE3	GT3	GT3	LE3	LE3	GT3	LE3	LE3	GT3
Medu	1	2	1	4	3	4	2	4	3	3	4
Fedu	3	3	1	2	2	3	2	3	2	3	3
Mjob	at_{home}	at_{home}	at_{home}	health	other	services	other	other	services	other	teacher
Fjob	services	services	services	services	services	services	teacher	teacher	teacher	teacher	teacher
reason	other	other	other	home	home	repu	home	home	home	home	repu
guardian	father	father	mother	father	father	uncle	mother	mother	brother	mother	mother
traveltime	2	2	1	0	1	1	1	1	1	1	1
studytime	3	4	2	4	2	2	3	2	2	2	2
famsup	yes	yes	no	yes	no	yes	no	yes	yes	yes	yes
paid	yes	yes	yes	yes	yes	yes	no	yes	yes	yes	yes
activities	yes	no	no	yes	no	yes	no	yes	no	yes	no
nursery	yes	no	yes	yes	yes	yes	yes	yes	yes	yes	yes
higher	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
internet	no	yes	yes	yes	no	yes	yes	no	yes	yes	yes
freetime	3	3	3	2	3	4	4	1	2	5	3
health	3	3	3	5	5	5	3	1	1	5	2
absences	6	4	10	2	4	10	0	6	0	0	0
Pstatus	T	T	T	T	T	T	T	T	T	T	T
famsup	no	no	no	yes	yes	yes	no	yes	yes	yes	yes
famrel	4	4	4	3	4	4	4	4	4	5	3
health	4	3	3	4	5	4	3	1	1	5	2
absences	6	4	10	2	4	10	0	6	0	0	0
aggression	yes	yes	no	no	yes	yes	yes	yes	no	no	yes
giving up	yes	yes	yes	no	no	yes	yes	yes	yes	no	no
LSC	yes	no	no	no	yes	yes	yes	no	no	no	yes
stress	no	yes	no	yes	yes	yes	no	yes	no	yes	yes
goout	4	3	2	2	2	2	4	4	2	1	3
G3 (CS)	8	7	10	4	8	6	7	6	9	10	5

Appendix A shows a sample from the psychological experiment based dataset. The First column of the Table (4) illustrates the attributes of the dataset while the rest of the columns show a sample of the values of these particular attributes. This sample table only shows those attributes of student performance which are related with propose multilayer model of SRC.

VI. THREATS TO VALIDITY

Working with student's skills prediction, we have reported some limitations. The proposed multilayer model of SRC is yet to evaluate for the enhancement of the CS measurement performance because simulating too many factors in the single study can make the proposed method imprecise. Furthermore, factors as frustration and its severity can be quantized to increase the scalability of the method, e.g., student's skills prediction during interviews and written examinations. In future work, we have to evaluate the prediction results (error between actual and predicted values) of each layer of the multilayer model of SRC. The other threats to validity are given below.

- To validate the performance of the current attempt, we have merged two datasets (1. publicly available [16] and 2. the second one is used by the literature [6]) to accurately investigate the accuracy of the method. Therefore, in the future work, the proposed method need to validate using more datasets. Besides, we have performed a series of experiments and then evaluated the technique on average performance in term of applied evaluation measures.
- Due to the highly nonlinear relationship between CS and SRC, we have partitioned CS-outcomes into groups (P1 to P4) while in the future work, we may need to simulate the statistical association between SRC and each component of CS-outcome.
- The current work has used the Gauss-Newton Algorithm (GNA) to estimate the unknown parameters of the model. Thus, applying other baseline methods (e.g., Bayesian Inference, RNN) may not provide the same results.

- We have worked on five layers of SRC; therefore, by using different values, someone may have different results.

VII. CONCLUSION AND FUTURE WORK

In the current study, we presented a multilayer Cognitive Skills (CS) measurement method that depends on the quantization of student's Study-related Characteristics (SRC). The contributions of the proposed approach are threefold. First, the method split SRC into five factors ((1) travel schedule between school and home, (2) study schedule, (3) outing schedule, (4) free timing, and (5) relationship between parents). To develop a multilayer approach, we assigned a specific range to each factor that initiated a five-layered model of SRC. Second, the method divided CS into 21 periodic intervals (with a period of 1). The division of SRC and CS is to enhance the accuracy and preciseness of the method. Third, the method used the Gauss-Newton Algorithm (GNA) to simulate the relationship between SRC layers and CS intervals. Resultantly, we achieved six mathematical equations for the multilayer model of SRC that successfully simulated the nonlinear relationship between CS and SRC. During the experiment, the proposed method was tested on two students' performance datasets. The results show that the proposed multilayer CS measurement method achieved significant precision, recall, F1 score and accuracy measures values.

APPENDIX A
SAMPLE OF DATA

See Table 4.

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REFERENCES

[1] E. A. Patall, R. R. Steingut, A. C. Vasquez, S. S. Trimble, K. A. Pituch, and J. L. Freeman, "Daily autonomy supporting or thwarting and students' motivation and engagement in the high school science classroom," *J. Educ. Psychol.*, vol. 110, no. 2, pp. 269–288, 2017.

[2] J. Härkönen, F. Bernardi, and D. Boertien, "Family dynamics and child outcomes: An overview of research and open questions," *Eur. J. Population*, vol. 33, no. 2, pp. 163–184, 2017.

[3] M. M. Al-Tarabily, R. F. Abdel-Kader, G. A. Azeem, and M. I. Marie, "Optimizing dynamic multi-agent performance in E-learning environment," *IEEE Access*, vol. 6, pp. 35631–35645, 2018.

[4] K. D. Rajab, "The effectiveness and potential of E-learning in war zones: An empirical comparison of face-to-face and online education in Saudi Arabia," *IEEE Access*, vol. 6, pp. 6783–6794, 2018.

[5] F. Orooji and F. Taghiyareh, "Peer assessment and self-assessment in social learning environments through a new crowd-sourced mechanism," *IEEE Access*, vol. 6, pp. 7321–7339, 2018.

[6] S. Ahmad, K. Li, H. A. I. Eddine, and M. I. Khan, "A biologically inspired cognitive skills measurement approach," *Biol. Inspired Cogn. Archit.*, vol. 24, pp. 35–46, Apr. 2018.

[7] A. Zollanvari, R. C. Kizilirmak, Y. H. Kho, and D. Hernández-Torrano, "Predicting students' GPA and developing intervention strategies based on self-regulatory learning behaviors," *IEEE Access*, vol. 5, pp. 23792–23802, 2017.

[8] J. Xu, K. H. Moon, and M. van der Schaar, "A machine learning approach for tracking and predicting student performance in degree programs," *IEEE J. Sel. Topics Signal Process.*, vol. 11, no. 5, pp. 742–753, Aug. 2017.

[9] R. V. Lindsey, M. Khajah, and M. C. Mozer, "Automatic discovery of cognitive skills to improve the prediction of student learning," in *Proc. Adv. Neural Inf. Process. Syst.*, 2014, pp. 1386–1394.

[10] S. D. Truscott *et al.*, "Creating consultee change: A theory-based approach to learning and behavioral change processes in school-based consultation," *Consulting Psychol. J. Pract. Res.*, vol. 64, no. 1, pp. 63–82, 2012.

[11] S. Clayton, C. Manning, K. Krygsman, and M. Speiser, *Mental Health and Our Changing Climate: Impacts, Implications, and Guidance*. Washington, DC, USA: American Psychological Association and ecoAmerica, 2017.

[12] G. W. Ladd, I. Ettekal, and B. Kochenderfer-Ladd, "Peer victimization trajectories from kindergarten through high school: Differential pathways for children's school engagement and achievement?" *J. Educ. Psychol.*, vol. 109, no. 6, p. 826, 2017.

[13] M. Stanton and R. Welsh, "Systemic thinking in couple and family psychology research and practice," *Couple Family Psychol., Res. Pract.*, vol. 1, no. 1, pp. 14–30, 2012.

[14] M. Spengler, R. I. Damian, and B. W. Roberts, "How you behave in school predicts life success above and beyond family background, broad traits, and cognitive ability," *J. Personality Social Psychol.*, vol. 114, no. 4, pp. 620–636, 2018.

[15] B. J. Lovett and L. J. Lewandowski, *Testing Accommodations for Students With Disabilities: Research-Based Practice*. Washington, DC, USA: American Psychological Association, 2015.

[16] P. Cortez and A. Silva, "Using data mining to predict secondary school student performance," Dept. Inf. Syst./Algoritmi R&D Centre, Univ. Minho, Braga, Portugal, Tech. Rep., 2008.

[17] Y. Wang and V. Chiew, "On the cognitive process of human problem solving," *Cogn. Syst. Res.*, vol. 11, no. 1, pp. 81–92, 2010.

[18] C. Qi *et al.*, "Facial expressions recognition based on cognition and mapped binary patterns," *IEEE Access*, vol. 6, pp. 18795–18803, 2018.

[19] W. Li, J. Wang, K. Chen, and W. Li, "An intelligent cognition method of human health states based on a variant knowledge granularity feedback mechanism," *IEEE Access*, vol. 5, pp. 19570–19580, 2017.

[20] K. Chen, J. Wang, W. Li, W. Li, and Y. Zhao, "Simulated feedback mechanism-based rotary kiln burning state cognition intelligence method," *IEEE Access*, vol. 5, pp. 4458–4469, 2017.

[21] M. Zorzi, A. Zanella, A. Testolin, M. De F. De Grazia, and M. Zorzi, "Cognition-based networks: A new perspective on network optimization using learning and distributed intelligence," *IEEE Access*, vol. 3, pp. 1512–1530, Aug. 2015.

[22] Y. Kim, T. Soyata, and R. F. Behnagh, "Towards emotionally aware AI smart classroom: Current issues and directions for engineering and education," *IEEE Access*, vol. 6, pp. 5308–5331, Jan. 2018.

[23] J. Zhu and Y. Zou, "Cognitive network cooperation for green cellular networks," *IEEE Access*, vol. 4, pp. 849–857, 2016.

[24] Q. Wu, L. Chen, Z. Wang, G. Ding, and L. Zhang, "Information measurement of cognitive communication systems: The introduction of negative cognitive information," *IEEE Access*, vol. 6, pp. 34288–34295, 2018.

[25] L. Kidziński, M. Giannakos, D. G. Sampson, and P. Dillenbourg, "A tutorial on machine learning in educational science," in *State-of-the-Art and Future Directions of Smart Learning*. Singapore: Springer, 2016, pp. 453–459.

[26] X. Chen, J. Yang, and G. Ding, "Minimum Bayesian risk based robust spectrum prediction in the presence of sensing errors," *IEEE Access*, vol. 6, pp. 29611–29625, 2018.

[27] A. S. Rodrigues, F. Bhering, C. A. De B. Pereira, and A. Polpo, "Bayesian estimation of component reliability in coherent systems," *IEEE Access*, vol. 6, pp. 18520–18535, 2018.

[28] F. Wang, J. Zhang, B. Lin, and X. Li, "Two stage particle filter for nonlinear Bayesian estimation," *IEEE Access*, vol. 6, pp. 13803–13809, 2018.

[29] J. Bobadilla, R. Bojorque, A. H. Esteban, and R. Hurtado, "Recommender systems clustering using Bayesian non negative matrix factorization," *IEEE Access*, vol. 6, pp. 3549–3564, 2018.

[30] X. Li, Y. Hu, E. Zio, and R. Kang, "A Bayesian optimal design for accelerated degradation testing based on the inverse Gaussian process," *IEEE Access*, vol. 5, pp. 5690–5701, Mar. 2017.

[31] S. Bergin, "Statistical and machine learning models to predict programming performance," Ph.D. dissertation, Dept. Comput. Sci., National Univ. Ireland, Maynooth, Ireland, 2006.

[32] M. Pojon, "Using machine learning to predict student performance," M.S. thesis, Fac. Natural Sci. Softw. Develop., Univ. Tampere, Tampere, Finland, 2017.
[33] Z. Iqbal, J. Qadir, A. N. Mian, and F. Kamiran. (2017). "Machine learning based student grade prediction: A case study." [Online]. Available: https://arxiv.org/abs/1708.08744
[34] A. S. Lillard, M. D. Lerner, E. J. Hopkins, R. A. Dore, E. D. Smith, and C. M. Palmquist, "The impact of pretend play on children's development: A review of the evidence," *Psychol. Bull.*, vol. 139, no. 1, pp. 1–34, 2013.
[35] S. A. Garbacz, L. L. McIntyre, and R. T. Santiago, "Family involvement and parent-teacher relationships for students with autism spectrum disorders," *School Psychol. Quart.*, vol. 31, no. 4, pp. 478–490, 2016.
[36] B. Y. Ohye *et al.*, "Three-generation model: A family systems framework for the assessment and treatment of veterans with posttraumatic stress disorder and related conditions," *Prof. Psychol., Res. Pract.*, vol. 46, no. 2, pp. 97–106, 2015.
[37] G. M. Fosco, M. J. Van Ryzin, A. M. Connell, and E. A. Stormshak, "Preventing adolescent depression with the family check-up: Examining family conflict as a mechanism of change," *J. Family Psychol.*, vol. 30, no. 1, pp. 82–92, 2016.
[38] T. Käser, A. G. Busetto, B. Solenthaler, J. Kohn, M. von Aster, and M. Gross, "Cluster-based prediction of mathematical learning patterns," in *Proc. Int. Conf. Artif. Intell. Educ.*, 2013, pp. 389–399.
[39] R. Zazo, P. S. Nidadavolu, N. Chen, J. Gonzalez-Rodriguez, and N. Dehak, "Age estimation in short speech utterances based on LSTM recurrent neural networks," *IEEE Access*, vol. 6, pp. 22524–22530, 2018.
[40] Z. Zhang and Z. Yan, "Hybrid-level joint-drift-free scheme of redundant robot manipulators synthesized by a varying-parameter recurrent neural network," *IEEE Access*, vol. 6, pp. 34967–34975, 2018.
[41] C. Yin, Y. Zhu, J. Fei, and X. He, "A deep learning approach for intrusion detection using recurrent neural networks," *IEEE Access*, vol. 5, pp. 21954–21961, 2017.
[42] A. Amin *et al.*, "Comparing oversampling techniques to handle the class imbalance problem: A customer churn prediction case study," *IEEE Access*, vol. 4, pp. 7940–7957, 2016.
[43] A. Hassan and A. Mahmood, "Convolutional recurrent deep learning model for sentence classification," *IEEE Access*, vol. 6, pp. 13949–13957, 2018.
[44] M. Lopez-Martin, B. Carro, A. Sanchez-Esguevillas, and J. Lloret, "Network traffic classifier with convolutional and recurrent neural networks for Internet of Things," *IEEE Access*, vol. 5, pp. 18042–18050, 2017.
[45] I. E. Livieris, K. Drakopoulou, and P. Pintelas, "Predicting students' performance using artificial neural networks," in *Proc. 8th PanHellenic Conf. Int. Participation Inf. Commun. Technol. Edu.*, 2012, pp. 321–328.
[46] S. Rovira, E. Puertas, and L. Igual, "Data-driven system to predict academic grades and dropout," *PLoS ONE*, vol. 12, no. 2, p. e0171207, 2017.
[47] Y. Liu *et al.*, "Collaborative learning team formation: A cognitive modeling perspective," in *Proc. Int. Conf. Database Syst. Adv. Appl.*, 2016, pp. 383–400.
[48] N. S. Newcombe *et al.*, "Psychology's role in mathematics and science education," *Amer. Psychol.*, vol. 64, no. 6, pp. 538–550, 2009.

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