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RESEARCH ARTICLE

Multi-Clustered Mathematical Model for Student Cognitive Skills Prediction Optimization

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ABSTRACT The outbreak of COVID-19 boosted the rapid increase in E-Learning platforms. It also paves the way for Massive Online Open Courses (MOOCs) to break the record for students' enrollment in online courses. In such circumstances, it is significant to timely identify at-risk students' Cognitive Skills (CS) through an optimized E-Health service. CS is profoundly influenced (negatively and positively) by many human factors, including anxiety and biological age group. Literature has massive findings that correlated CS with anxiety and ageing. However, the earlier studies contributed to CS prediction algorithms are still limited and not up to the mark to efficiently estimate CS under the umbrellas of anxiety and age clusters. The CS prediction system requires an optimization algorithm to mathematical model the influence of age and anxiety clusters. This work predicts students' CS under the influence of anxiety and age clusters, referred to as the Anxiety and Ageing (AA) mathematical model. It solves threefold challenges. First, the study quantizes students' CS, age, and the adverse effects of anxiety. Second, it iteratively computes CS with respect to the anxiety cluster and further revises it under the influence of the age cluster. Third, the study provides a novel data collection method for future researchers by demonstrating assumption-based datasets. The prediction results manifest that the current model achieved excellent precision, recall, and F1 score performance.

INDEX TERMS Cognitive skills prediction, data analytics, prediction optimization, data-driven approach, mathematical modeling.

I. INTRODUCTION

After the outbreak of COVID-19, society realized potential challenges in proposing a feasible Students Cognitive Skills (CS) prediction system to identify the reason behind at-risk students' performance. Recent statistics show that the research on pandemics reported an alarming circumstance for at-risk students. Their CS is profoundly influenced (negatively and positively) by many human factors, including anxiety and age group. Another significant phenomenon is social media which increases parents' expectations, and students' anxiety [1], [2], [3], [4]. Parents notice the excellent achievements of other students, and they also try to prepare their children for competition. Such a phenomenon increases the severity of anxiety, which negatively impacts the CS of students during cognitive tasks, i.e., assignments, quizzes, and examinations. Such activities need a student to process the information and give a response. So, the computation of students' CS is essential for academic tutors and parents to fulfil their desires. Also, institution management can oversee career counselling programs for at-risk students, which evaluate students' performance and help place them in a specific group during cognitive activities.

The conventional prediction models cannot satisfy the global change in education due to the COVID-19 pandemic [5]. The Massive Open Online Courses (MOOCs) offer a variety of online courses to enhance students' performance; however, it also introduces new challenges, such as

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accurate quantization of students' CS and mathematical modeling of anxiety and age. Psychological studies statistically associate weak CS with different human factors, e.g., anxiety and age. [6], [7], [8]. Also, biological aging [9], [10] has a distinct role (it can be negative or positive) while students are performing the aforementioned cognitive tasks using their CS [11]. Previous work offers a variety of findings that directly or indirectly contributed to students' CS prediction [12], [13], [14]. Such competitive contributions provide opportunities for a better understanding of students' significant factors and performance prediction during critical cognitive activities. They are flooded with several statistical findings that correlated CS with anxiety and age. Such results create opportunities for the development of a significant CS computation system. Earlier contributions reveal a small amount of work on synchronization and coordination among the students' prediction system contributions [15], [16], [17].

These works are still limited to addressing the following challenges:

1. Quantize and digitize the adverse effects of anxiety, age, and CS clusters for parameter estimation.
2. Predict CS, which is affected by the adverse effects of anxiety and age cluster.
3. Synchronization is needed to predict CS under the cumulative impact of anxiety and age clusters.
4. Iterative computation of CS while considering the extensive impact of anxiety and age.

This study proposes an Anxiety and Ageing (AA) mathematical model to solve the current challenges in students' CS prediction systems. This study presents an Anxiety and ageing mathematical model to solve the current challenges in students' CS prediction systems. First, it defines the CS cluster while assigning a unique range to CS outcomes. Second, the model is split into two main clusters, i.e., the anxiety cluster and the combined cluster of anxiety and age. The anxiety cluster is classified into three effects that perform a key role in influencing student CS. On the other hand, the age factor is split into five distinct ages as they perform different actions on students' CS. The model learned the statistical association between students' age, anxiety, and CS further validated on a students' score dataset. Eventually, the results manifest significant performance in terms of state-of-the-art measures.

II. EARLIER CONTRIBUTIONS

Examining the correlation between students' CS and biologically inspired factors is required to highlight students' strengths and weaknesses. Such factors include but are not limited to frustration, anger, anxiety, gender, biological ageing, etc. They positively or negatively impact CS when students perform cognitive tasks, such as attempting assignments, class activities, quizzes, and examinations. Here, the literature contributions are two-fold. First, the study considers psychological data analysis and data mining findings, and second, it assesses the existing students' CS prediction methods to understand the motivation of the current attempt clearly.

A. RELATIONSHIP BETWEEN COGNITIVE SKILLS AND INFLUENTIAL FACTORS

Articles depict that Cognitive Skills (CS) are always affected by an individual's surroundings, i.e., interaction with family members, traveling distance with the institute, interaction with classmates and teachers, ageing, various emotions (e.g., anxiety), and experience [18], [19]. These major influential factors drive CS during cognitive tasks. Psychology has reported significant work on various emotions, such as anxiety, stress, and frustration [20]. Data analysis fields provide quantitative findings to statistically associate the influential factors with students' CS. They reflect major contributions to emphasize different issues and challenges in students' weak performance; however, each factor mentioned above is challenging due to their multifaceted nature and sensitivity. The individual' CS system is a knowledge processing system that manipulates different characteristics and human factors. CS react based on the influence of environmental and biological factors [21].

Moreover, prior studies are saturated with the number of research contributions that associate the biologically inspired characteristics with the CS level of an individual [22], [23]. They demonstrate that students' CS has a nonlinear association with the biologically inspired factors during cognitive tasks. These factors continuously affect (positively or negatively) the cognitive outcome of an individual, such as exhaustion due to multiple times of failures in different competitions. It shows that we need an algorithmic solution to measure the influence of biologically inspired factors. Such algorithmic ideas can be achieved from the earlier feature studies [24], [25]. Also, we need to achieve a CS prediction model to predict CS under the influence of various human factors; however, it is only possible when a prediction system learns the sensitive nature of natural ageing and students' anxiety. Earlier studies evaluated the statistical association between students' performance and the influencing factors, which paved the way for an effective CS prediction system, i.e., a correlation between anxiety, ageing, and students' CS.

B. PERFORMANCE PREDICTION SYSTEMS

With a CS prediction system, students can experience their weak CS. Literature studies deliver many techniques to process different influential factors statistically associated with students' CS. A few of them are as follows. In [26], the researchers worked on brain-inspired cognitive architecture. A list of challenges has been addressed while interacting with brain-related factors. In [27], the authors illustrated the fundamental deficiencies and limitations of different cognitive frameworks, which also report various cognitive models and architectures with a list of potential challenges. They also claim that the most important step is to advance the earlier cognitive models. According to [28], we need to efficiently quantize those factors which have a strong statistical association with CS, such as accurate quantization of emotional attributes. Therefore, we need insightful analysis to establish an association between ageing, gender, frustration, anxiety, and environmental factors. The environmental factors include but are not limited to exposure, parents' profession, and study schedules. Moreover, the study [29] investigated distinct CS prediction systems.

The earlier approaches lack quantization approaches (i.e., quantization of biologically inspired factors), which are the main point of inspiration for the current study [30]. Effective CS prediction systems are in dire need of in-depth quantization of biologically inspired factors such as anxiety and ageing. Therefore, the current approach has initiated an iterative solution to modulate anxiety effects and the age group of students. The literature manifests that brain processes and cognitive functionalities direct the CS level of students. Therefore, the main focus of computer scientists is to replicate the concept of a human natural cognitive system [31]. It shows that we are in dire need of human brain functionalities replication to achieve an effective solution for students' CS prediction.

Predicting CS of students enables school management to detect weak students and help them recover their problems. In such cases, the recommendation of a psychologist or a tutor plays a crucial role in enhancing their CS. Also, students with poor CS need to reschedule the study timing. Such CS prediction methods depend on biologically inspired environmental and emotional factors. The environmental factors consist of two variables as mother's job and exposure. Besides environmental factors, the study schedules of a student and the parent's cohabitation status profoundly influence academic achievements [32], [33]. Literature depicts adequate studies that present CS prediction systems using emotional and environmental factors, i.e., frustration, exposure, and mother profession [34]. Such prior approaches have produced effective solutions to predict students' CS; however, they have different limitations and threats to validities, i.e., quantization of anxiety, biological ageing, and computing the influence of anxiety and age.

C. LIST OF CHALLENGES TO SOLVED

The existing studies are insignificant in achieving a CS prediction model while considering the following challenges.

- Quantize and digitize anxiety and age clusters as well as CS for parameter estimation.
- Predict CS under the influence of anxiety and age clusters. So, synchronization is needed to predict CS under the cumulative impact of anxiety and age.
- Iterative estimation of CS while considering the influence of anxiety and age cluster.

The study depicts that the previous methods failed to address the above challenges while considering anxiety and age. Also, the featured studies are saturated with the number of contributions that have associated some essential human attributes with CS of a student [35], [36], [37], [38], [39]. These students' characteristics dictate the expected cognitive outcome during critical circumstances, i.e., interviews, examinations, and class activities.

The earlier studies' contribution gives us meaningful opportunities for the insightful investigation of CS, students' factors, and the CS prediction system; however, the synchronization and coordination among the existing studies are still missing. So, consequently, the related studies proposed meaningful approaches to formulate CS during cognitive tasks; however, the limitations mentioned above become the primary source of inspiration for the quantization of anxiety and ageing to develop an influence computation model.

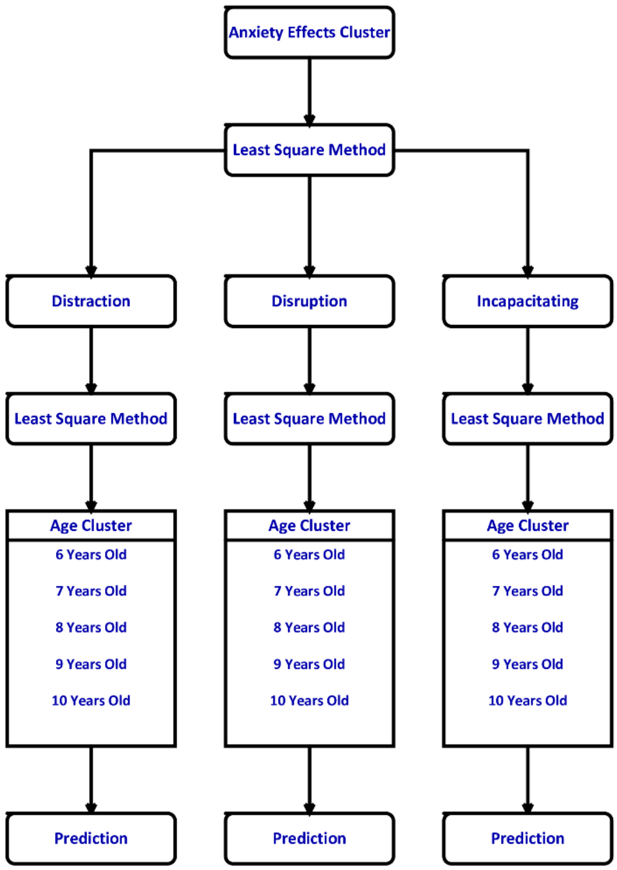

FIGURE 1. Framework of anxiety and ageing mathematical model.

III. PROPOSED ANXIETY AGING MATHEMATICAL MODEL

First, we quantize CS for the in-depth estimation of students' CS prediction; therefore, a unique range is assigned and divided into non-periodic intervals, i.e., $0 \leq CS \leq 10$. Second, the anxiety is split into three effects, which has increased the transparency of anxiety influence, i.e., $Anxiety_{eff}$. Also, a detailed framework of the proposed methodology is provided in Figure 1. The relationship between CS and anxiety effects is hypothesized by the following equation.

$$Anxiety_{eff} \alpha \frac{1}{CS} \tag{1}$$

$$(ddi)\alpha\frac{k}{CS} \tag{2}$$

Equation (1) represents the nonlinear relationship between anxiety effects $Anxiety_{eff}$ and CS. Also, it hypothesizes that anxiety effects are inversely proportional to students' CS outcomes. In Equation (2), anxiety effects are divided into three effects ddi and a constant k.

It represents distraction, disruption, and incapacitation of a student respectively. This design is initiated to test non-periodic intervals of CS under the influence of anxiety. Also, the specific set of ageing is classified into five outcomes, i.e., from 6 years to 10 with a 1- year periodic space (6, 7, 8, 9, 10). Such a component-wise division reflects unbiased parameters estimation because the relationship between influencing factors and CS intervals is highly nonlinear. Eventually, the following sections describe the parameter learning process with the least square method.

A. MATHEMATICAL MODEL

The first hypothesis depicts that there is an insightful correlation between age, anxiety, and the non-periodic intervals of CS. Now to properly investigate these relationships, we need to apply statistical methods. The second hypothesis shows that the correlation between age, anxiety, and students' performance is quite nonlinear. The study uses regression-based the on least square method to report the influence of various factors. This method gives good estimates of the new parameter estimation and simulation with relatively small data sets. $Anxiety_{eff}$ represents a list of anxiety effects (i.e., distraction, disruption, and incapacitating). We use a fitting technique to identify the values for parameters β_i and to find the statistical connection between age, CS, and anxiety. To achieve the goal of parameter estimations, we use and further extend the Michaelis Menten model.

$$cs\left(Anxiety_{eff}, \beta_{ij}\right) = \frac{\left(\beta_{ij}\right)\left(Anxiety_{eff}\right)}{\left(\beta_{ij} + Anxiety_{eff}\right)} \tag{3}$$

In Eq (3), $Anxiety_{eff}$ shows list of the effects of anxiety as well as ageing. Therefore, the initial try is performed to report the particular density of $Anxiety_{eff}$ and age_i(students can have ages from 6 years to 10 years). Thus, through this process, the estimation of parameters (β_i) has been achieved. Additionally, the next section identifies the residual of prediction process.

$$SE = \sum_{i=1}^{m}\left(cs - f\left(Anxiety_{eff}, \beta_{ij}\right)\right)^2 \tag{4}$$

Eq (4) examined the prediction error (SE) among the actual students' performance (cs), weights and the predicted values. Such parameters estimation and correlation investigation enable us to learn about the negative and positive effect of age_i, $Anxiety_{eff}$ on students' performance cs. Table 1 illustrates the parameters values. During nonlinear least squaring, we developed a specific range for the parameters such as anxiety and age, which is given in Table 1. Next, the specific

TABLE 1. Range of values.

Cluster	Specific Parameters	Intervals
Anxiety (effects)	$Anxiety_{eff}$	$0.5 \leq Anxiety_{eff} \leq 5$
age	age	$6 \leq age \leq 10$

variables as anxiety and age are observed, which are the main predictors and contributors in the following equation.

$$cs\left(age, Anxiety_{eff}\right) = \frac{\{age+\ EE\ \}\,\theta\lambda}{(s)\sum_{j=1}^{n}\left(Anxiety_{eff}\right)} \tag{5}$$

In Eq (5), the age reveals the estimated interval of age, $Anxiety_{eff}$ shows effects of anxiety, EE represents parameters for experience and exposure. The θ and λ are weights (parameters) achieved for gender descriptions (constants). Also, the severity of anxiety s is reported as constant. Thus, Eq (5) manifest the proposed model equation which successfully simulated the nonlinear relationship between CS, age, and anxiety. Also, the specific ranges of parameters and predictors are given in Table 1.

Algorithm 1 Computing Cognitive Skills Using Anxiety and Ageing Clusters

```
Data: sets, Anx, ageing.
Data: SP.
Result: SP.
initialization;
    foreach i in Anx do
        Compute SP with respect to i using Eq (3).
    end
    foreach k in ageing do
        Update SP with respect to k using Eq (5)
    end
Calculate Prediction Loss
  if the accuracy is not satisfactory then
   Updated Bij, EE, θ, λ
    foreach m in Anx do
      Update SP with respect to m using Eq (3)
    end
    foreach n in ageing do
      Update SP with respect to n using Eq (5)
    end
  else
      Return refined SP
  end
```

B. PROPOSED ALGORITHM

Algorithm (1) illustrates the iterative procedure of the proposed mathematical model. As an input, it takes three sets of data; 1) Anx has the information about anxiety's effects, and 2) SP shows students' performance outcomes

TABLE 2. Pearson correlations.

	Distraction	*Disruption*	*Incapacitation*	*age*
Severity 1: Pearson Correlation	1			
Severity 2: Pearson Correlation	.486**	1		
Severity 3: Pearson Correlation	.373**	.524**	1	
Severity 4: Pearson Correlation	.295*	.287*	.548**	1

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

during training. First, the loop initiates a set of iterations in which i picks the anxiety effects from Anx set (one by one). Students' performance SP is computed under the influence of anxiety effects. Such computation is performed using Eq (3).

Second, another loop selects k from *ageing* set to optimize the value of SP via Eq (5) based on age cluster. Lastly, Algorithm (1) compares the predicted value with an actual value of SP using Eq (4). Thus, this process is continued until the technique achieves maximum accuracy for the students' performance predictions.

C. ASSUMPTION-BASED DATASET

The proposed Anxiety ageing mathematical model was trained and validated on an assumption-based students' performance dataset. Here the data collection format of [40] was assumed to produce random values for the validation of the proposed model. Yamane (1967) was followed for sampling selection, which explains enough samples from the targeted population. The Yamane formula for sampling is given below.

$$n = \frac{N}{1 + N\left(e^2\right)} \tag{6}$$

According to the Yamane sampling formula (using population), the minimum sample size is 16800; however, the current dataset consists of 25000 instances to ensure the Yamane standard. Moreover, the correlation between anxiety effects, ageing, and CS is highlighted by Pearson correlation table 2. The table is self-explanatory with Pearson correlation values and confidence intervals.

D. MODEL TRAINING

The training of AA Mathematical model has been initiated with the ten folds' cross validations procedure. We have chosen the 10 folds of the experimental analysis based on 6 instances of ages (from 6 years to 10 years), three effects of anxiety, and one normal condition. Normal condition is added for comparative analysis purposes. A significant accuracy has been obtained in terms of the validation model. Furthermore, 150 specific tests were obtained for the ten groups of sample data to achieve accurate parameters. The number of observations during the training of AA mathematical was carried out in various pairs, such as 80:20, 70:30, 85:15, 60:40, 90:10, 75:25, 90:10, 70:30, 60:40, and 70:30 (pairs for k-folds' cross validation). Lastly, the average performance was computed as a prediction result. The proposed model was trained using the training set in this section.

E. STATISTICAL ALGEBRAIC EVALUATION

The AA mathematical model finds the values of CS based on anxiety effects and ageing. The mathematical evaluation is give below.

$$DisT^{k+1} = CS.DisT^{k} \tag{7}$$

$$A6 = CS.DisT^{k+1} \tag{8}$$

$$\begin{bmatrix} DisT^{k+1} \\ A6 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} DisT^{k} \\ DisT^{k+1} \end{bmatrix} \tag{9}$$

Eq (7) to Eq (9) reflects the statistical association between distraction ($\mathrm{Dis}^{\mathrm{Tk+1}}$) and age = 6 (A6).

$$DisT^{k+1} = CS.DisT^{k} \tag{10}$$

$$A7 = CS.DisT^{k+1} \tag{11}$$

$$\begin{bmatrix} DisT^{k+1} \\ A7 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} DisT^{k} \\ DisT^{k+1} \end{bmatrix} \tag{12}$$

$$DisT^{k+1} = CS.DisT^{k} \tag{13}$$

$$A8 = CS.DisT^{k+1} \tag{14}$$

$$\begin{bmatrix} DisT^{k+1} \\ A8 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} DisT^{k} \\ DisT^{k+1} \end{bmatrix} \tag{15}$$

$$DisT^{k+1} = CS.DisT^{k} \tag{16}$$

$$A9 = CS.DisT^{k+1} \tag{17}$$

$$\begin{bmatrix} DisT^{k+1} \\ A9 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} DisT^{k} \\ DisT^{k+1} \end{bmatrix} \tag{18}$$

$$DisT^{k+1} = CS.DisT^{k} \tag{19}$$

$$A10 = CS.DisT^{k+1} \tag{20}$$

$$\begin{bmatrix} DisT^{k+1} \\ A10 \end{bmatrix} = \begin{bmatrix} CS0 \\ 0CS \end{bmatrix} \times \begin{bmatrix} DisT^{k} \\ DisT^{k+1} \end{bmatrix} \tag{21}$$

Furthermore, Eq (10) to Eq (21) shows the step by step iterative modeling of distraction (Dis^{Tk+1}) effect of anxiety and different age groups of students (A7 = 7 years old, while A10 = 10 years old). The following equations depict the step by step iterative strong correlation between disruption and various age groups.

$$DisRu^{k+1} = CS.DisRu^{k} \tag{22}$$

$$A6 = CS.DisRu^{k+1} \tag{23}$$

$$\begin{bmatrix} DisRu^{k+1} \\ A6 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} DisRu^{k} \\ DisRu^{k+1} \end{bmatrix} \tag{24}$$

$$DisRu^{k+1} = CS.DisRu^{k} \tag{25}$$

$$A7 = CS.DisRu^{k+1} \tag{26}$$

$$\begin{bmatrix} DisRu^{k+1} \\ A7 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} DisRu^{k} \\ DisRu^{k+1} \end{bmatrix} \tag{27}$$

$$DisRu^{k+1} = CS.DisRu^{k} \tag{28}$$

$$A8 = CS.DisRu^{k+1} \tag{29}$$

$$\begin{bmatrix} DisRu^{k+1} \\ A8 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} DisRu^{k} \\ DisRu^{k+1} \end{bmatrix} \tag{30}$$

$$DisRu^{k+1} = CS.DisRu^{k} \tag{31}$$

$$A9 = CS.DisRu^{k+1} \tag{32}$$

$$\begin{bmatrix} DisRu^{k+1} \\ A9 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} DisRu^{k} \\ DisRu^{k+1} \end{bmatrix} \tag{33}$$

$$DisRu^{k+1} = CS.DisRu^{k} \tag{34}$$

$$A10 = CS.DisRu^{k+1} \tag{35}$$

$$\begin{bmatrix} DisRu^{k+1} \\ A10 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} DisRu^{k} \\ DisRu^{k+1} \end{bmatrix} \tag{36}$$

Eq (22) to Eq (36) shows the step by step mathematical iterative modeling of disruption (*DisRu*) and ageing (A6 = 6 years old, A10 = 10 years old). Finally, Eq (37) to Eq (55) reflect the statistical association among Incapacitating (*IncT*) and five age groups.

$$IncT^{k+1} = CS.IncT^{k} \tag{37}$$

$$A6 = CS.IncT^{k+1} \tag{38}$$

$$\begin{bmatrix} IncT^{k+1} \\ A6 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} IncT^{k} \\ IncT^{k+1} \end{bmatrix} \tag{39}$$

$$IncT^{k+1} = CS.IncT^{k} \tag{40}$$

$$A7 = CS.DisT^{k+1} \tag{41}$$

$$\begin{bmatrix} IncT^{k+1} \\ A7 \end{bmatrix} = \begin{bmatrix} CS0 \\ 0CS \end{bmatrix} \times \begin{bmatrix} IncT^{k} \\ IncT^{k+1} \end{bmatrix} \tag{42}$$

$$IncT^{k+1} = CS.IncT^{k} \tag{43}$$

$$A8 = CS.IncT^{k+1} \tag{44}$$

$$\begin{bmatrix} IncT^{k+1} \\ A8 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} IncT^{k} \\ IncT^{k+1} \end{bmatrix} \tag{45}$$

$$IncT^{k+1} = CS.IncT^{k} \tag{46}$$

$$A9 = CS.IncT^{k+1} \tag{47}$$

$$\begin{bmatrix} IncT^{k+1} \\ A9 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} IncT^{k} \\ IncT^{k+1} \end{bmatrix} \tag{48}$$

$$IncT^{k+1} = CS.IncT^{k} \tag{49}$$

$$A10 = CS.IncT^{k+1} \tag{50}$$

$$\begin{bmatrix} IncT^{k+1} \\ A10 \end{bmatrix} = \begin{bmatrix} CS & 0 \\ 0 & CS \end{bmatrix} \times \begin{bmatrix} IncT^{k} \\ IncT^{k+1} \end{bmatrix} \tag{51}$$

$$Anx_i = (Mt)(var) \tag{52}$$

So, in eq (52), i = 3 and every $Anx_i = 2$. Let's suppose, $Anx_i \in R^{+2}$ and $\overline{Anx_i} \in R^{+2}$, then we have the following proof.

$$\begin{aligned} \left\| \mathrm{Anx}_i - \overline{\boldsymbol{Anx_i}} \right\| &= \left\| (\mathrm{Mt})(\mathrm{var}) - (Mt)(\overline{\boldsymbol{var}}) \right\| && (53) \\ &= \left\| \mathrm{Mt}.(var - \overline{\boldsymbol{var}}) \right\| && (54) \\ &\leq \left\| \mathrm{Mt} \right\| \left\| (var - \overline{\boldsymbol{var}}) \right\| && (55) \end{aligned}$$

IV. MODEL EVALUATION

The experiment section validates the performance of the proposed AA mathematical model. This section is further divided into the following subsections.

A. VALIDATION SET

The training data sets (using 10-folds cross-validations) are already used for the model building, while the validation sets are used for the performance analysis of the proposed model.

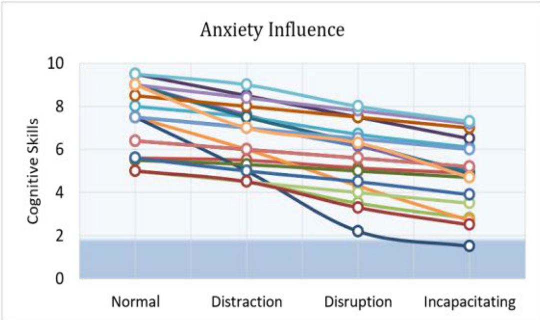

FIGURE 2. Three effects of anxiety decrease the outcome of CS.

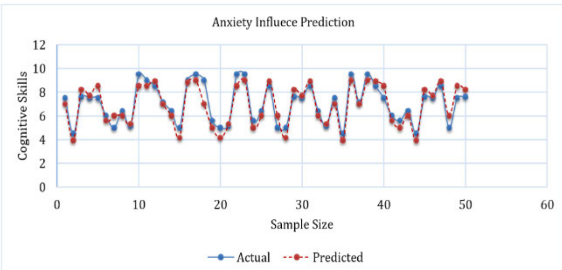

FIGURE 3. Prediction performance with respect to anxiety effects.

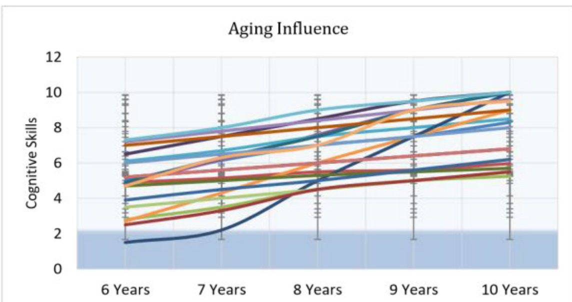

FIGURE 4. Students' CS is increasing with ageing.

In order to achieve accurate performance analysis, we have selected three types of tests (i.e., prediction of the influence of anxiety and ageing) as well as prediction accuracy using a random sample. The following sections describe the aforementioned test results.

B. PREDICTION OF ANXIETY INFLUENCE

During the prediction of anxiety influence, a random sample consists of anxiety to only process the impact of anxiety effects (i.e., distraction, disruption, and incapacitating). Additionally, the actual data shows that the effects of anxiety continuously decrease CS outcomes. Thus, the predicted values should follow the relationship between anxiety effects and CS.

The performance of the mathematical module for anxiety was measured in terms of different accuracy measures, i.e., precision, recall, and F1 score. Precision is the fraction of accurately predicted values between the absolute predicted values (correct and incorrect). On the other hand, recall is

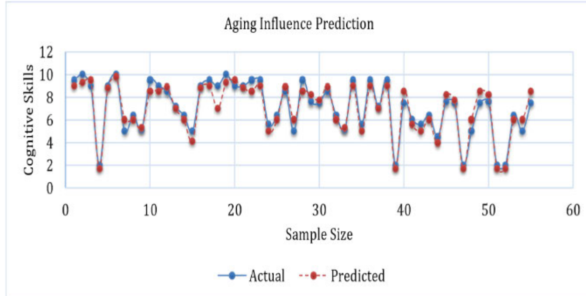

FIGURE 5. Prediction performance with respect to ageing.

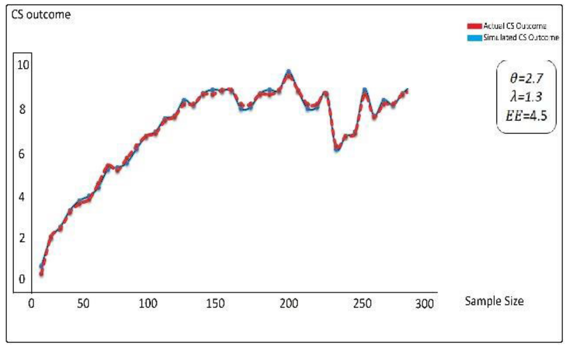

FIGURE 6. Accuracy of the CS simulation model: The red continuous line represents simulated values while the blue line shows actual values. The graph also shows the range of parameter values while the rest of the variables had shown in Table 1.

TABLE 3. Prediction performance.

Measured CS Samples	Precision	Recall	F1 Score
Anxiety Influence	0.812	0.809	0.8121
ageing Influence	0.793	0.808	0.7855
Anxiety and ageing Influence Sample	0.799	0.805	0.7911

the fraction of accurately predicted values that have been predicted over the total amount of valid instances. Thus, precision and recall measures are based on the measure of relevance. The current matrix consists of true positive (TP) and false positive (FP). Also, the prediction validation process can have true negative (TN) and false-negative (FN). The study achieved precision with the following model.

$$Precision = \frac{(TP_i)}{TP_i + \sum_{i=1}^{3} (FP_i)} \tag{56}$$

In Eq. (56), TP illustrates true positive, FP manifests false positive, TN shows true negative, and the FN represents false negative. The Eq. (56), measures the precision of the proposed model. It has obtained 0.812 as a precision for the selected sample of the data. Also, we have achieved recall for

TABLE 4. Comparison with prior studies.

Features	*Proposed Model*	*Earlier Study [41]*	*Earlier Study [42]*	*Earlier Study [43]*	*Earlier Study [44]*	*Earlier Study [45]*
Cognitive Skills Range Quantization	0 to 10	Not mentioned	Score mentioned	Assignment Score on LMS	MOOC Score	Not Mentioned
Division of anxiety into effects	3 effects	No	No	No	No	No
Student's Age quantization	5 levels (6 to 10 with 1 year of periodic interval)	No	No	No	All categories	Higher Education students
Baseline Method	Michaelis Menten model	Markov property and Attention mechanism	Hidden Markov Model	No	Hill-climbing, maximum likelihood estimation method, and Genetic Algorithm	4-layer stacked LSTM network, Random Forest, Gradient Boosting
Predicting Cognitive Skills with respect to Anxiety effects and age level	Yes	No	No	No	Performance Prediction with respect to various student-related features	OULAD dataset
Prediction process	Iterative with memorization of previous CS value	Bidirectional LSTM	No	No	Iterative	Iterative Architecture
Major Characteristics	Quantization of CS, anxiety effects and age. Gives interesting idea of novel data collection for students' CS prediction	Exercise-Enhanced Recurrent Neural Network, Bidirectional LSTM, Exercise-aware Knowledge Tracing	Comparative analysis findings	Analysis of Decision tree, naive Bayes, logistic regression, multilayer perceptron, and SVM on the bases of student performance prediction	Base-line method consist of three algorithm: Hill-climbing, maximum likelihood estimation method, and Genetic Algorithm	Combination of base-line methods.
Scalability	Yes with adding more parameters	Not explained	Not explained	Not explained	Yes	Yes
Evaluation with number of accuracy measures	4	2	1	1	1	1

the predicted value while using the following equation.

$$Recall = \frac{(TP_i)}{TP_i + \sum_{i=1}^{3} (FN_i)} \tag{57}$$

Eq. (57) measures the recall of the predicted values of the selected sample set. It has produced 0.809 as a recall for the influence model. Also, the last accuracy measure is referred to as the F1, which is shown by the following model equation.

$$F1 = 2 \times \frac{Precision \times Recall}{recision + Recall} \tag{58}$$

Eq. (58) computes the F1 score of the proposed model. It has achieved 0.8121 as an F1 score while evaluating the selected sample. The performance result shown in Table 2 illustrated that the proposed influence computation model had achieved significant accuracy in terms of the accuracy, as mentioned earlier measures. Figure 1 represents that the CS is decreasing with the addition of anxiety effects. Such a relationship was simulated with the proposed model. Figure 2 represents that the CS is decreasing with the addition of anxiety effects. Such a relationship was simulated with the proposed model. Also, Figure 3 manifests that the outcome of CS continuously decreases with the addition of anxiety effects.

C. PREDICTION OF AGEING INFLUENCE

A random sample is selected to validate the performance that comprises the data of ageing and students' CS outcomes (with non-periodic intervals). The relationship between students' CS and biological ageing is positive, which means that CS increases with an increase in a student's age. The model performance was evaluated using Eq. (6), (7), and (8), which has distinct values for the precision, recall, and F1 score. Table 2 illustrates the performance measures values, which show that the proposed model achieved maximum accuracy. Moreover, Figure 4 manifests that the students' CS increases with ageing, which needs to be simulated. Also, Figure 5 represents the outcomes of CS under the influence of different age categories, which means that CS is improving with a year-wise increase in students' age.

D. PREDICTION OF ANXIETY AND AGEING INFLUENCE

This section discusses the prediction results obtained from a random sample consisting of anxiety effects, ageing, and students' scores. The model's performance was assessed during the validation process using four types of accuracy measures, i.e., Mean Forecast Error (MFE), precision, recall, and F1 score. First, we have applied MFE to obtain performance accuracy.

$$MFE = \frac{\sum_{i=1}^{n} (e_i)}{n} \tag{59}$$

In Eq (59), e represents error in cs_{actual} - $cs_{simulated}$. The MFE (0.087) value manifests that AA mathematical model has achieved significant accuracy (91.3%). In addition, Figure 6 reports the graph of comparison and visualization of the model accuracy.

Second, we have measured the performance accuracy of the proposed influence model while applying precision, recall, and F1 score. Table 1 manifests the accuracy results for the measures as mentioned earlier.

V. COMPARISON WITH EARLIER STUDIES

The proposed Anxiety Ageing Mathematical model has been compared with three competitive approaches. The comparison is made upon different features and solved challenges. The study already discussed multiple findings and features in the introduction and literature review section; however, a concise demonstration of comparative analysis is provided in the self-explanatory Table 4. It depicts that the current study is compared with earlier methods through 9 significant features. As literature highlighted many technical challenges and efforts toward student performance prediction; however, they were unable to achieve various features (mentioned in Table 4).

VI. LIMITATIONS

Along with multiple contributions, this study reported a few limitations: follows. First, the proposed AA Mathematical Model is instead a journey than a destination; therefore, the primary limitation is the lack of extensive comparison based on prediction accuracy, which is planned in the future (Table 4 consists of a list of novelty and contributions). Second, we have yet to perform extensive empirical tests using a few more real-world datasets to ensure prediction accuracy. Third, statistical associations among students' anxiety and age will be investigated through Electroencephalography (EEG) in the future. A few more limitations are given below.

- During the model validation process, a series of experiments were conducted to validate the model's performance. Finally, we have chosen the average prediction results (i.e., see model validation section).
- The current model produces different results with different parameter values, which will also affect the accuracy.

VII. CONCLUSION

The current attempt demonstrates the Anxiety Ageing (AA) mathematical model to predict students' Cognitive Skills (CS) while formulating anxiety and age clusters effects. To achieve the goal of CS prediction, it solved threefold challenges. First, it quantized and digitized the clusters of anxiety, age, and CS for parameter estimation. Second, the influence of anxiety and age cluster was synchronized to predict CS under the cumulative impact of anxiety and age. Third, it ensured an iterative estimation of CS while considering the influence of anxiety and age. During validation of the model, the study provides a novel data collection method for future researchers via demonstrating real-world and oversampled datasets. The results showed that the proposed model achieved excellent performance in terms of state-of-the-art measures, i.e., precision, recall, and F1 score.

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CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest to report regarding the present study.

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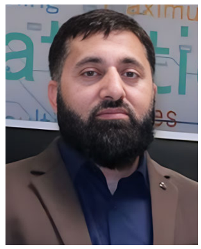

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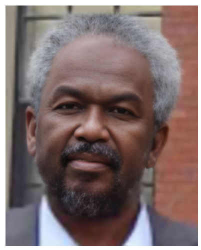

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