

# Artificial Intelligence-Enabled Interactive System Modeling for Teaching and Learning Based on Cognitive Web Services

Humin Yang, Fuyang Normal University, China\*

Achyut Shankar, Amity University, India

Velliangiri S., CMR Institute of Technology, India

## ABSTRACT

The future of modern education and web-based learning is inherently associated with the advancement in modern technologies and computing capacities of new smart machines, such as artificial intelligence (AI). AI is a high-performance computing environment powered by special processors that use cognitive computing for machine learning and data analytics. There are major challenges in online or web-based learning, such as flexibility, student support, classification of teaching, and learning activities. Hence, this paper proposes smart web-based interactive system modeling (SWISM) based on artificial intelligence for teaching and learning. The paper aimed to categorize learners according to their learning skills and discover how to enable learners with machine learning techniques to have appropriate, quality learning objects. Furthermore, local weight, linear regression, and linear regression methods have been introduced to predict the student learning performance in a cloud platform.

## KEYWORDS:

Artificial Intelligence, Interactive system modeling, learning, Teaching, web-based learning

## INTRODUCTION

Artificial intelligence (AI) has been a significant focus in recent years in the modern teaching field, with the hope that it remains one of the key goals for future-oriented schools and educators (Hinojo-Lucena et al., 2019). It facilitates individualized learning and real-time feedback. Several AI-enabled applications and programs allow students to better understand and integrate concepts in areas for learning (Yoon et al., 2019). The stages vary from class assistants with AI to insightful. AI systems that best track the success and reversal of an individual student (Haristian et al., 2019). AI will push performance, optimization, and streamline admin tasks to provide teachers with flexibility, independence (Miyaji et al., 2019), and comprehension of special capabilities for human machines (Abdel-Basset et al., 2019). The AI view in education strives together for the best outcomes for

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\*Corresponding Author

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students, incorporating computers and teachers' best abilities (How et al., 2019). At every level of education, information and communication technologies (ICTs) play a critical role in enhancing learning and teaching in the SWISM framework. In developed countries, it is widely accepted that ICTs have enhanced educational standards based on cognitive web services for machine learning and data analytics (Shakeel et al., 2020). Artificial intelligence technologies can assist people with language differences or impaired hearing or visual access to global classrooms (Yoo et al., 2019). AI helps break down silos between schools and classrooms (Kumar et al., 2019). An instructor needs much time to assess homes and assessments (Acevedo et al., 2018). At the same time, AI joins and works efficiently on these assignments while guiding the learning gaps (Selvakumar et al., 2016). It is proposed in this paper that Smart Web-based Interactive System Modeling (SWISM) can be used to overcome these problems. Teachers and reflection facilitators could seamlessly access students' digital devices via cloud platforms. Teachers can use cognitive web services for machine learning and data analytics to encourage students to engage in reflective activities.

AI education technologies, including learner AI tutors, smart curriculum creation, and a new way of creating individuals for educators through virtual global conferences, are being developed (Elazab et al., 2015). In schooling, social connections play a significant part. Interacting with others has been very helpful in allowing the student to coordinate his/her thinking, focus on his perception, and recognize differences in logic (Loukatos et al., 2019). Innovative and intelligent web-based educational systems created new and exciting work on AI-based education (Alvarez-Dionisi et al., 2019). The web presents a motivation to extend a broader spectrum of AI technology to education (Ullah Z et al., 2020). Promote contact between the student and the teacher by and the communication between the teacher and the student (offering various approaches to the teacher, including e-mail address, social media accounts, and telephone numbers) [16]. Providing reviews in good time or rapidly (response to students) (Beltrán-Velasco et al., 2020). They provide students with straightforward and accurate instructions on all actions (Maedche et al., 2019). There are other well-established techniques for students to feel their confidence and participation throughout the course (How et al., 2019).

E-learning is a formalized learning framework based on interactive tools (Fahimirad et al., 2018). The use of computers and the Internet forms the key component of e-learning through instruction that can be done in or out of the classes (Davila-Guzman et al., 2019). E-learning can be called a network that enables sharing skills and information (Ikedinachi et al., 2019). The education distribution is done simultaneously or at altered times to many receivers (Umachandran et al., 2019). Interactivity eLearning is described as a "dialogue" between learners and eLearning (Wilhelm et al., 2019) tools in which learners engage and participate in the eLearning method (Sánchez J et al., 2020). Online or web-based or E-learning saves time and money (Ramadhani et al., 2019). With online learning, learners can access content remotely and at any time (Gadola et al., 2019). E-learning is cost-effective; businesses save a considerable amount on transport and lodging expenses for both learners and teachers [28], as well as on-site and supplies (Ryu et al., 2019).

In this paper, Smart Web-based Interactive System Modeling (SWISM) has been proposed based on artificial intelligence in teaching and learning for students. The paper purposes classify learners' characteristics according to their learning skills and discover how to enable learners with machine learning techniques to have appropriate, quality learning objects. Moreover, this paper introduces the machine learning algorithm, such as Local weight Linear Regression. Linear regression methods have been introduced to predict student learning performance in a cloud platform.

The major contributions of the paper are,

- Smart Web-based Interactive System Modeling (SWISM) is based on artificial intelligence in teaching and learning for students via cognitive web services.
- Machine learning algorithms for predicting the student's preference for learning and performance, such as linear regression and local weight linear regression.

- Students' preferences and learning outcomes can be better predicted with the SWISM model's data analytics and machine learning, thanks to the improved accuracy.

The rest of the study is decorated as follows: section 1 discusses the introduction and existing interactive teaching and learning methods for students. In section 3, Smart Web-based Interactive System Modeling (SWISM) has been suggested based on cognitive web services for machine learning and data analytics. In section 4, numerical results have been performed. Finally, section 5 concludes the research paper.

## LITERATURE WORKS

(Zamora-Polo et al., 2019) discussed artificial intelligence in education (AIED). Learning Analytics and algorithmic or human-based guidance, and Learning Analytics and Computational Learning. The study is formulated as follows: first, they describe AI and learning analytics and differentiate them from Educational Data Mining (EDM) and machine learning. Discourse review shows a diametrical connexion between the conventional educational model and the modern notion of schooling and technology transfer. Artificial intelligence-based learning programmes, lack of data control, ambiguity, and lack of data comprehension are all issues that fuel discussion on AI-based learning programmes, which hinders the development and deployment of effective solutions.

(Haryanto et al., 2019) suggested the Modeling, prediction, and classification of student academic performance utilizing artificial neural networks (ANN). Conventional mathematical analyses are constrained in making accurate educational content forecasts. This study proposed ANN for predicting and classifying student academic performance Output of the NN model is measured by error rate, regression, error histogram, uncertainty matrix, and area under the ROC. The NN model's overall accuracy of 84.8% can be expected; there are some caveats to consider.

(Alvarez-Dionisi et al., 2019) discussed Smart learning utilizing personalized recommendations in web-based learning systems utilizing an artificial bee colony algorithm to enhance learning performance. In this study, a novel architecture, i.e., a customized bee-recommender for e-learning (PBReL) focused on ABC optimization, is suggested to construct a recommendation system using K-means clustering. Other suggested programs have made usage of an artificial bee colony to define the ideal learning path. Moodle, the learning management system, is used to conduct the research (LMS).

The results demonstrate that the suggested system achieves better accuracy and scope.

(Tadejko, 2020) discovered the age of big data and cognitive technologies is upon us. Compared to normal datasets, big data creates new opportunities to explore new values, allowing us to understand the intangible assets better and bring new challenges. Machine learning, IoT sensors, data analytics, and cognitive machines emulating human intelligence must be added to the cloud and computing ecosystem to adjust to these new technological changes. New technologies on smart clouds and supercomputers are explored here, and big-data theories.

Services computing technologies are expected to benefit greatly from artificial intelligence (AI). Numerous significant achievements in computing frameworks and systems, big data analytics, and online and smartphone networks have accelerated recent research (Yau, 2021). Many aspects of this subject matter will be addressed by an esteemed panel, including how to effectively incorporate AI into smart, resilient manufacturing, how to develop secure web applications against powerful attacks, and a few examples from real-world use cases

This paper proposes smart web-based interactive system modeling (SWISM) based on artificial intelligence in teaching and learning to overcome these issues. Teacher guidance and a reflection facilitator could be provided seamlessly via cloud platforms to students' digital devices. Therefore, teachers may encourage reflective activities based on cognitive web services for machine learning and data analytics. This study suggested a cloud-based learning environment to help educators and

students build and improve reflection during and after classes to meet this goal. The following section discusses the proposed SWISM method briefly.

### **Smart Web-Based Interactive System Modeling (SWISM)**

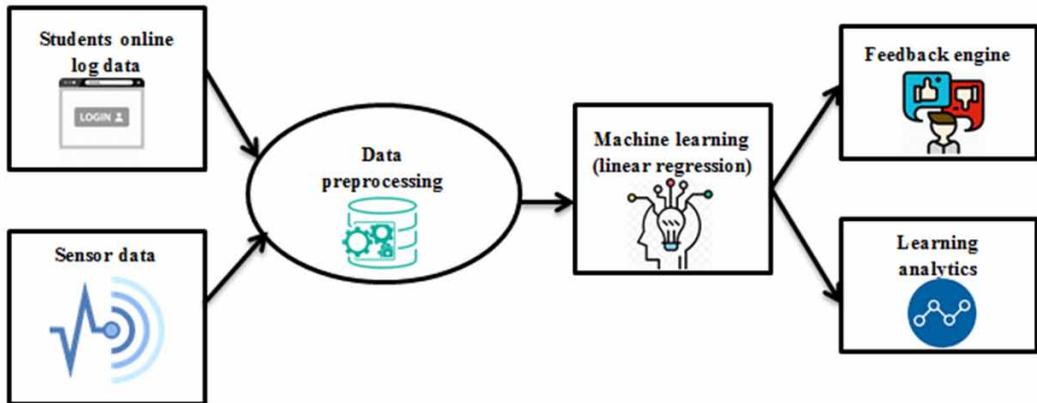
In this paper, Smart Web-based Interactive System Modeling (SWISM) has been proposed based on artificial intelligence in teaching and learning for students. In today's academic world, artificial intelligence brings a long way to turn the conventional ways of communicating information into an integrated learning environment using virtual and augmented reality (AR) technologies. A regular class can become a fascinating experience by increased realism in the classroom. The AR technology offers interactive examples to endorse textbook materials and includes gaming elements. This increases the instructiveness of groups. AR allows students to recall details that they have learned. Compared with other media such as books, videos, and seminars, improving learning efficiency and teaching efficiency has been demonstrated by integrating interactive technologies such as Augments of Reality, virtual reality (VR), and mixed reality (MR). Interactive study material, including text and media files, can be readily exchanged by focus groups and can be used conveniently with the help of smart devices. It's a natural progression from descriptive analytics. The help of simulation and optimization algorithms provides ideas for improving an existing procedure or system. Advanced analytics specifies a set of outcomes for each measurement, such as the maximum combination of means in a class, when dealing with software components and measurements in recent advances in cognitive web services for machine learning and data analytics

Because of the use of information and communication technology (ICT) and the accumulation of ICT's importance for today's teachings and learning, many educational institutions use the web to facilitate teaching and learning in different ways. Web-based learning (WBL) is referred to as online learning since it provides material for online classes. Education technologies provide innovative ways to coordinate instruction for teachers and allow for interdisciplinary activities. Various web-based approaches have been predicted to improve teaching student techniques. Much web-based learning literature indicates that technology (e.g., inadequate access, slow downloading) is one of the principal obstacles to using instructional resources instead of learning content design. Teachers need professional assistance on web-based learning preparation, design, and technical issues delivery. The process can be designed and used to construct interactive course content such as self-evaluations, animations, and simulations using "plug-ins" programs downloaded from the Internet. This can enhance education and are more fun and beneficial to students. Smart web-based interactive system modeling (SWISM) is proposed in this paper to address these issues. Teachers and reflection facilitators could easily access students' digital devices via cloud platforms. Teachers can use machine learning and data analytics to help students engage in reflective activities.

For example, it will split physical distances by enabling the training of learners scattered around learning areas; learners have access to courses through the online or learning management system that can enable them to decrease travel time and expenses, encourage interaction with students and teachers (asynchronous or synchronous), offer flexibility to engage. Web-based or online or E-learning is the complete learning activity, and teaching depends on computer management settings built from network IT techniques with interactive systems. The advantages of web-based learning are a student is in focus and autonomous, independent of time and location, cost-effective, unlimited access to content, knowledge sharing, and reuse. The Web-based learning environment provides general information about the unit of study and different resources, including definitions, synopsis, extended reading, scenarios demonstrating concepts (snapshots), and interactive forums. This paper examines Web-based instruction by artificial intelligence, both learning and teaching, explore the issues and possibilities, including E-classrooms and Web-supported instruction.

Figure 1 shows the architecture of the proposed SWISM method based on Artificial Intelligence. Artificial intelligence plays a main role in education. It supports educators in determining the drivers of students' performance and their weaknesses, implementing personalized and interactive student

Figure 1. The architecture of the proposed SWISM method based on Artificial Intelligence



models based on adaptive learning systems, knowledge level utilizing artificial intelligence to deliver predictive methods and tracking the student's progress in higher education. There is no one-size-fits-all approach to education because each student brings unique qualities to the classroom. An interactive student model or a learner model is created from these functions in cognitive web services for machine learning and data analytics. Creating a learner model is accomplished through a process known as user modeling. Students' strengths and weaknesses are identified, adaptive learning systems are used to implement personalised and interactive student models, and artificial intelligence is used to deliver predictive methods. Students' progress in higher education using this technology from figure 1.

The adaptive learning framework uses adaptation models. In other words, an adaptive learning system benefits from individual knowledge presented in the learner model to make the student's learning materials (learning, training, testing, etc.) and teaching methods suitable. However, the learner model is very important for adaptive learning systems and other adaptive uses.

In the interactive system modeling, the learners work in groups with the virtual or augmented device. The individual design of various learning pointers with sensors. In this collaborative phase, the learners benefit from the knowledge contributions of learners in the examination.

Self-pacing, multimedia formats, course management, and adaptable feedback functions provide qualities shared by all delivery media. In addition, the innovative features of online teaching, modular alteration of courseware, broad usability, and web connection to similar content. Web-based instruction delivers multi-dimensions to utilize in training and education environments. These comprise facilitating and promoting enrollment into courses, a program of instruction or availing the syllabus, submitting, and posting assignments, communicating with students and instructors, teamwork on assignments, and constructing learning communities. A learning community is a small group of students who share similar academic interests and work in partnership with one or more professors in the classroom. When properly designed, learning groups create an ecosystem where everyone engages in a cycle of reflection, problem-solving and application to achieve new aims. Creating one from the ground is to understand the advantages of learning communities.

The web has become a useful tool for distance learning and learning. The intrinsic flexibility enables implementation in some ways, from the basic administration of courses and the supervision of students to completing lessons online. Each of these uses functions for a different purpose. When assessing the use of the Internet, those purposes should be identified. An instructor, for example, can teach from one person to the next and publish a classroom curriculum, tasks, and ratings on the web. Three metrics have been used for evaluating the performance of the user interface system: time on task, several errors, and help frequency. Teachers are best known for teaching the students they care for.

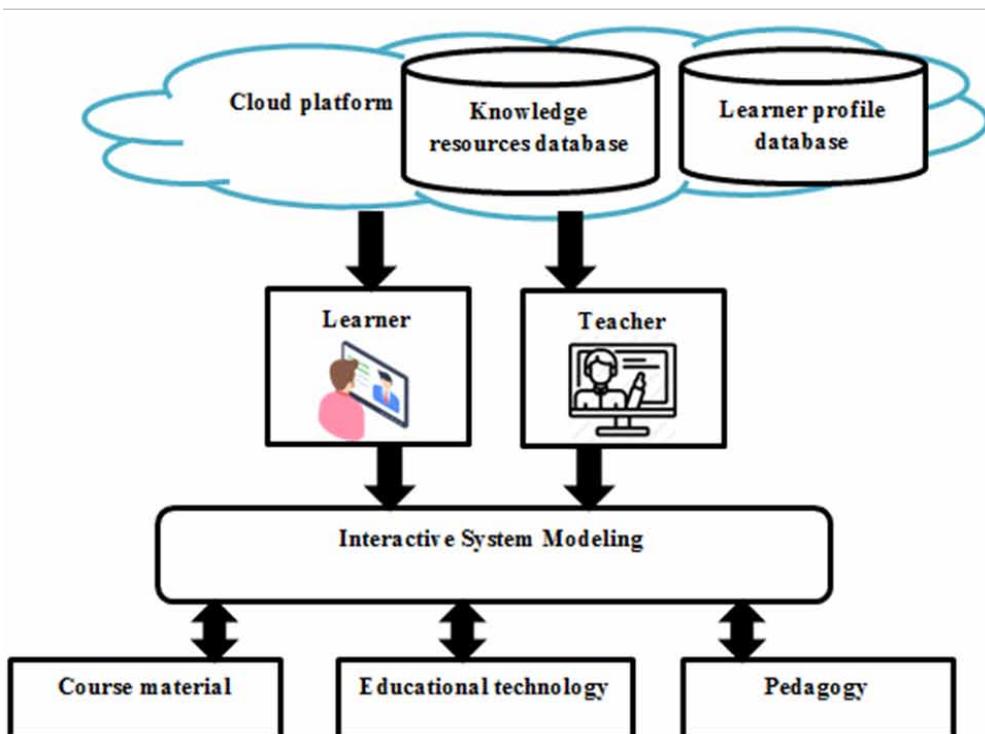
Moreover, in the classroom, teachers play a variety of other roles. Teachers set the tone of their classes, create a warm atmosphere, offer feedback, and support to students and become role models. Students will feel passion for the subject in any live online teaching and interaction in virtual school. Excellent online teachers are very excited about getting students interested in the curriculum. An online teacher has to play a leading role in one or more online learning experiences. There was a mistake. This allows the instructor to spend more time teaching the students and less time teaching. The instructor ensures that the students concentrate on important concepts and ideas.

Another element in the success of online learning is the role of the teacher. Generally, three roles are a motivator, a marketing specialist, and a technology resource person. Teachers have to spend time planning, and teachers must make sure that students participate actively in the learning process.

Figure 2 shows the proposed interactive system modeling. According to the SWISM, most learning systems have an adjustment mechanism and dynamic feedback. School systems with the best results have high expectations for students' abilities. They help their teachers understand their students' needs in cognitive web services for machine learning and data analytics. They gradually moved away from managerial oversight and accounting to professional modes of job organization. They encourage their teachers to be innovative, improve their own and their colleagues' achievements, and improve their knowledge of best practices. The proposed method of the SWISM highlights and emphasizes the importance of the equilibrium conception through coordination and interaction among the different components, which is focused on up-to-date and dynamic data, including relevant technology, course content, pedagogy, and the initial profile of the students that the skills and differences of the students required are both established and balanced.

Depending on the suggested swims model, learners are evaluated regularly. The marking is automatically completed for suitable subjects, and the individual dynamic workbooks, textbooks, and exercises are built in line with the evaluation, concentrating on learners' knowledge. The

Figure 2. The proposed Interactive system modeling

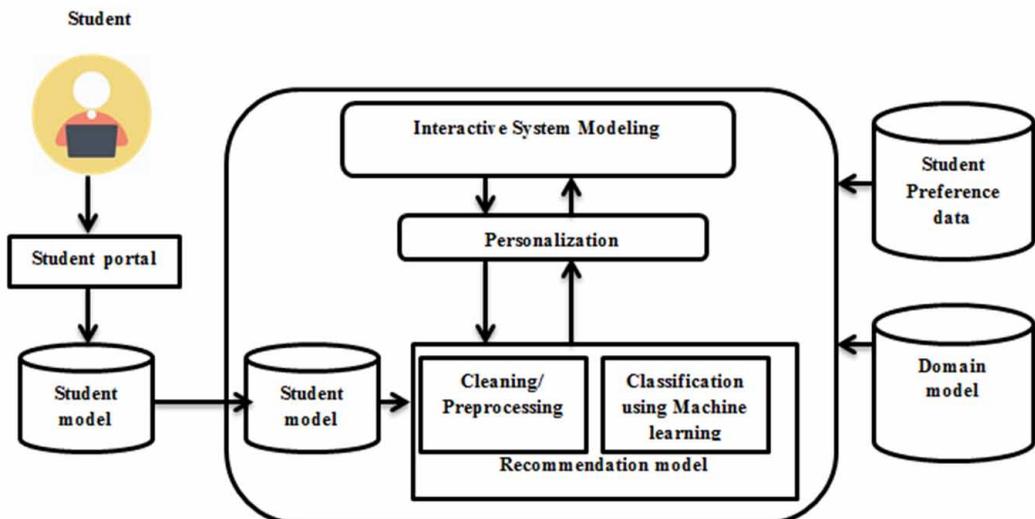


proposed SWISM method highlights and stresses the significance of the balancing conception via the coordination and interaction among the various constituents of the model based on up-to-date and dynamic data comprising relevant technology, course material, pedagogy, and learners' original profile to both develop skills and accommodate students' dissimilarities needed in a balanced and relevant manner. It is proposed that the SWISM method emphasises and emphasises the importance of the equilibrium conception by coordinating and interacting among the various components, which are focused on current and dynamic data, including relevant technology, course content, pedagogy, and the initial profile of students that the skills and differences of the required students are both established and balanced. It aids in creating learning systems considering multimedia presentation considerations, human-computer interaction design principles, and decisions about interaction level, interaction type, and teaching styles to be utilized following various contents, dissimilar students, and AI technologies utilized. A user's interaction with the resource is marked by a two-way route where the actions accurately learn goals or results generated on each side are affected. Software resource design must take account of the relevant effects of this interaction, and the implementation of special techniques to enhance this interaction with the user must follow usability criteria.

It is constantly updated with good interaction practice knowledge. SWISM involves students with a diversity of interactions with peers, experts, and materials.

Figure 3 shows the student model. This work aims to utilize an ML algorithm to categorize the students based on their learning preferences, sort them to a learning style class, and advise appropriate learning objects in a web-based education environment. The suggested system is structured into three fundamental components: The domain model, the student model, and the recommender system. Data-driven strategic decisions can now be made by organizations using this technology. The operational and cultural data is used to build predictive models. They build the models by extracting affiliations and other underlying connections from the data in cognitive web services for machine learning and data analytics. These three components interact, categorize the students, and discover a learning path to deliver accurate learning objects. A learner profile is a unique feature that leads to success in learning practices. The student profile provides details of how the student performs improved. It is generated by employing a questionnaire or a behavioral analysis via learning management. The student log file for a course is intended to construct a student profile in our study. The collected data is stored in a classifying algorithm to understand learner preferences such as virtual, auditory, read/

Figure 3. Student Model



writing, and kinaesthetic. The personal profile is static data about the student like Name, Id, and course enrolled. From figure 1, AI has a significant impact on education. Personalized and interactive student models based on adaptive learning systems help educators identify the factors that influence students' performance and implement personalised and interactive student models. Student learning preferences will be categorised. Appropriate educational materials will be recommended to students in an online education environment using an artificial intelligence algorithm in figure 3. Learning preference is a student's personal preference, a unique student distinction. This data is found from the log data of the student, which supports classifying the student and delivering the learning path of personalization with accurate learning goals. Personalized learning systems enable faculty members to take responsibility for their learning experience. In classrooms focused on students, they learn at their own pace to satisfy their needs and desires. This toolkit will explain how you can promote individual learning in all its forms through digital platforms and curricula to improve student participation and progress.

$$Y_j = \{y \in [0,1]\} \quad (1)$$

As discussed in equation (1), where  $Y$  is the likelihood of learning preference of  $j$ th learning style. The  $y$  value is allocated by a statistical value zero or one, where one denotes minimum satisfaction, and one indicates maximum satisfaction. The learning style individualities are allocated with statistical by examining the log data of the student the number of visits completed by the student to the learning goals. The student data has been gathered from the teacher-side application or smart device like watches; the cloud platform can profoundly examine and forecast the learning performance based on the ML algorithms by mentioning the outcome of students' response, instant feedback, group competition, the conduct prediction, and physical data for future learning scores. Besides, the model can correspondingly enable learning recommendations and teaching advice for teachers and learners. Particularly, two prediction approaches have been leveraged with regression analysis of score prediction known as local weights linear regression and linear regression. The major variance between the two prediction approaches is that linear regression estimates a single weight value for every student. Local weights linear regression determines the weight value independently that matches every learner's outcomes to predict the accurate score. The coefficient indicates how much the dependent variable can rise as the independent variable increases and leaves all the other independent variables stable. This paper introduces all prediction methods with a score prediction retrograde analysis such as linear regression and linear regression at local weights. The key difference between the two prediction methods is each student calculates very few weight values. In contrast, linear weights are determined independently of the weight value, which is consistent with the performance of any student to predict the correct score. Furthermore, every recognized model will fine-tune the weights to create the predicted score interval accurately.

For the collected data from class interaction, it computes the examination scores, the total class circumstance, and all-class weight, and then takes the weight value into the subsequent functions and builds a model:

$$x = \theta_0 + \theta_1 Y_1 + \theta_2 Y_2 + \theta_3 Y_3 + \theta_4 Y_4 \quad (2)$$

$$\begin{cases} \sum x = m\theta_0 + \theta_1 \sum y_1 + \theta_2 \sum y_2 + \theta_3 \sum y_3 + \theta_4 \sum y_4 \\ \sum y_1 x = \theta_0 \sum y_1 + \theta_1 \sum y_1^2 + \theta_2 \sum y_1 y_2 + \theta_3 \sum y_1 y_3 + \theta_4 \sum y_1 y_4 \\ \sum y_2 x = \theta_0 \sum y_2 + \theta_1 \sum y_1 y_2 + \theta_2 \sum y_2^2 + \theta_3 \sum y_2 y_3 + \theta_4 \sum y_2 y_4 \\ \sum y_3 x = \theta_0 \sum y_3 + \theta_1 \sum y_1 y_3 + \theta_2 \sum y_2 y_3 + \theta_3 \sum y_3^2 + \theta_4 \sum y_3 y_4 \\ \sum y_4 x = \theta_0 \sum y_4 + \theta_1 \sum y_1 y_4 + \theta_2 \sum y_2 y_4 + \theta_3 \sum y_3 y_4 + \theta_4 \sum y_4^2 \end{cases} \quad (3)$$

$$\hat{\theta} = (Y^T Y)^{-1} Y^T \mathbb{Y} \quad (4)$$

As shown in equation (2), (3), and (4), where  $x$  denotes the score of the test,  $y_1$  indicates the instant question score,  $y_2$  denotes the handwritten response,  $y_3$  denotes group competition outcome and  $y_4$  denotes the personal exercises. This can compute the most appropriate coefficients in the class. In conclusion, utilizing the matrix operation in equation (3), the weight values are evaluated as a regression model. The most accurate coefficients in the class can be derived using this. To summarise, the weight values are evaluated as a regression model in equation (3) for machine learning and data analytics using the matrix operation in that equation. Machine learning algorithms make up the vast majority of advanced learning algorithms. The majority of the algorithms for advanced learning fall under the machine learning algorithm category of learning. The process predicts an algorithm based on the previously entered values and results. Assume an input  $x$ 's and the output 'y' variable where  $y$  is an  $x$   $y=m\{x\}$  function. Local weight linear regression reads the value of variable  $x$ 's and variable 'y' that it can subsequently predict a very specific output of 'y' from the value entered by 'x.' The results of experiments show that a high interaction, learning efficiency, satisfaction, predictive ratio concerning other current methods is achieved through the proposed SWISM process. Because of the students' high level of awareness and interest in the subjects covered, AI-based solutions can be tailored to their specific needs of SWISM is used in an AI-based system. Students benefit from the method's weaknesses. Due to its limitations, provide educational content based on recent advances in cognitive web services for machine learning and data analytics.

Performance assessments are typically carried out by a manager, e.g., line managers or front-line managers. Annual performance reviews were reportedly too unusual to make feedback valuable, and argument is typically more detrimental than good for performance reviews. It is an aspect of the structure for the principal-agent defining the relation of knowledge between the employer and the employee and the direct impact and reaction when performance assessment occurs. The true value is the value derived by observing or calculating the data available. Faculty-student interactions have a significant impact on student's academic self-concept and motivation. Students and professors will always have a special relationship.

The observed value is known; the prediction is the value of the expected variable based on the regression analysis. Precision is how close the model predictions are to the observed values. The closer the data points to the forecasts, the more accurate the model. When you have an imprecise model, the observations are more distant from the forecasts, thereby decreasing the utility of the forecasts. To minimize the imprecision of these predictions, local weighted linear regression has been used to provide every earner with their weights; then, more precise prediction of prospect scores expressed as

$$I(\theta) = \sum_j \omega^{(j)} \left( x^{(j)} - \theta^T y^{(j)} \right)^2 \quad (5)$$

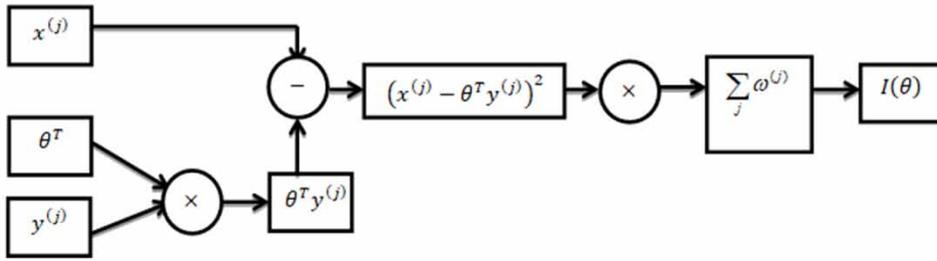
Equation (5) and figure 4 shows the accurate prediction of future scores, which denotes linear regression with the corresponding weight, which yields the regression outcome of local weight linear regression. The exact prediction of future scores, which suggests linear regression with the corresponding weight and results from local linear regression, is shown in equation (5) and figure 4.

$$\omega^{(j)} = \exp \left( - \frac{\left( x^{(j)} - y \right)^2}{2l^2} \right) \quad (6)$$

$$\hat{\theta} = \left( Y^T S Y \right)^{-1} Y^T S \mathbb{Y} \quad (7)$$

Artificial intelligence helps accomplish, adapt and streamline management tasks that teachers can understand and adapt in time and flexibility. Equation (6) indicates the exponential decay function

Figure 4. Accurate prediction of future scores



that can alter the value of  $l$  to determine the better-predicted model. In conclusion, the matrix operation in equation (7) can determine the coefficients that fit every learner and build a different prediction score model. Teachers can use artificial intelligence to accomplish, adapt, and streamline management tasks quickly and flexibly. The exponential decay function shown in Equation (6) can change the value of  $l$  and thus determine the best-predicted model.

Students who perform poorly or well may find it difficult to predict their scores because of this difficulty in recognizing when their performance is more obvious or needs improvement when compared to the overall class average in cognitive web services for machine learning and data analytics. A performance evaluation is a tool for documenting and assessing an employee’s work output. Performance evaluations are an important part of the profession’s development and are carried out daily in organizations from equation 4 to 6.

Algorithm for quantitative analysis in SWISM

Start

Identification of events;

Calculate the expected value ( $ev$ );

Compare magnitudes( $mt$ );

*If events(result == max ev)*

Find mean and variance;

*Else events(result != max ev)*

Identify risks;

Find coefficients;

Return output value;

$$ev = \{y \in [0,1]\} * (Y^T Y)^{-1} Y^T \mathbb{Y} * \frac{1}{\sqrt{mt}} \tag{8}$$

$$mt = \sum y_1 x + \sum y_2 x + \sum y_3 x + \sum y_4 x * (1 - ev) \tag{9}$$

From the above algorithm1, the three components of data analytics are the same regardless of the subject matter: data collection and loading, methodologies and algorithms, and an algorithmic framework that implicitly incorporates best practices and workloads based on the identification of events from equations (8) and (9). The datalogging and loading transaction flow the preparation and loading of input data into the computational platform by expected value  $ev$ . Data analysis methods and algorithms are provided by the component methods and algorithms with magnitudes  $mt$ . As a

final step, the computational system brings it together, providing interfaces for both users and other implementations to interact with it.

The expected value is used to prepare and load input data into the computational platform during the data logging and loading transaction flow. The magnitudes component methods and algorithms provide data analysis methods and algorithms. Finally, the computational system brings it together, allowing users and other implementations to communicate via user-friendly interfaces.

$$\frac{1}{\sqrt{mt}} = \exp\left(-\frac{\left(X^{(j)} - y\right)^2}{2t^2}\right) \theta_0 + \theta_1 Y_1 + \theta_2 Y_2 + \theta_3 Y_3 + \theta_4 Y_4 \quad (10)$$

Teachers will be able to use artificial intelligence to help with performance, customization, and streamlining administrative tasks because of their students' awareness and interest in the subject matter. The method uses its vulnerable sides to support students, and it provides instructional content based on its limitations. The student conducts the test before beginning using the software; for example, the app is evaluated and provided.

The proposed Smart Web-based Interactive System SWISM Modeling ()based on artificial intelligence in teaching and learning for students achieves high interaction, learning performance, satisfaction, and prediction ratio compared to other existing methods based on cognitive web services for machine learning and data analytics.

## Numerical Results and Discussion

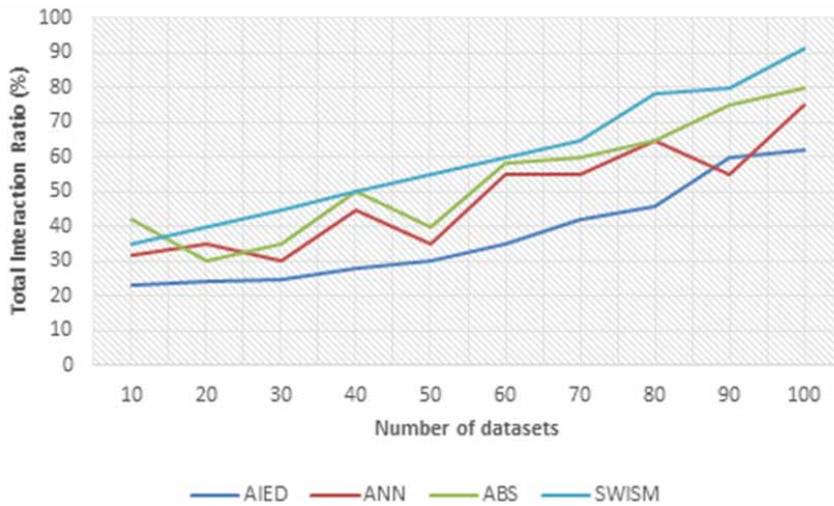
### *Total Interaction Ratio*

In face-to-face instruction, teachers have the opportunity for participation, active learning, discussion, and monitoring their learners' progress. These key components of student interaction with teachers should be used on the Internet or web-based courses. Students' self-esteem improves due to interactions between teachers and students in cognitive web services for machine learning and data analytics. The development of students' academic self-concept, as well as their motivation and progress, are greatly enhanced by interactions between students and faculty. There will always be a bond between students and professors. The proposed SWISM method based on artificial intelligence enhances the interaction ratio between student and teacher compared to other existing methods. Figure 5 demonstrates the total interaction ratio using the suggested SWISM model.

### *Learning Performance Ratio*

Web-based instruction in education and training expands; more people understand how necessary it is to measure its impact on student results, like student satisfaction and learning performance. By eliminating the spatial and temporal barriers, web learning environments have made learning much more convenient. This paper carried out a test to check the effect of the interactive student outcomes of the proposed method on student success to assess the interactive results based on the handwritten test, group competitions, instant questions, etc., collected in the proposed framework for the evaluation of the learning process. The proposed artificial intelligence-based SWISM method includes the knowledge consequences of a learner's knowledge conceptions in the recommendation database. These performance results evaluated a learner's skill in accomplishing a task or practice, retaining in terms of the learning durability after a period of instruction. Look at the class-wide test results to see the answers for trends. Business analysts look at data from the organization's perspective and concentrate on gleaning useful information. In this new field of analytics, called "visual analytics," the goal is to use interactive visual interfaces to aid analytical reasoning. Pay special attention to

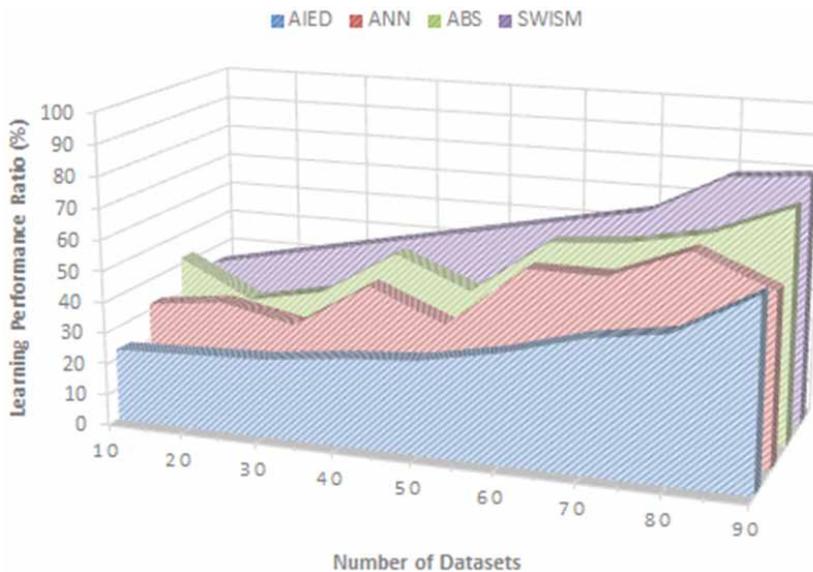
Figure 5. Total Interaction ratio



areas with issues for many students. Check your course plans then. Traditional learning evaluation strategies typically arise at the end of the term when a transition is too late. Evaluation strategies that build up students’ learning engagement include: integrating several evaluation methods. Provide task-including feedback continuously. Build fruitful fighting opportunities.

E-learning programs are customized according to the needs and expertise of the learner and are the main element in the learning process. Personalized suggestions e-learning systems should tailor their learning experience to individual learners’ objectives. Prior awareness has long been recognized as the primary impact factor in learning and student success. The sum and consistency of previous experience affect the retention of knowledge and the ability to apply analytical problem-solving skills of a higher order. Figure 6 shows the learning performance ratio using the proposed SWISM method.

Figure 6. Learning Performance Ratio



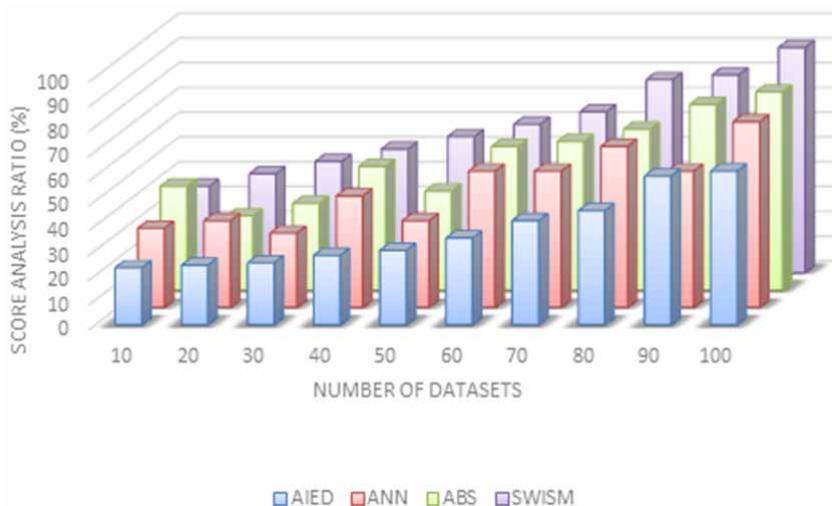
## Score Analysis

For the analysis and students' grades prediction, figures 6 shows the results between the forecasted and original scores by linear regression and local weight linear regression, correspondingly. Local linear regression and linear regression approaches were used to predict the output of students in a cloud network. Test results show that the suggested cloud analytical model SWISM offers intelligent learning recommendations, student preference prediction and learning efficiency. Database systems for data stores and warehouses will soon include more advanced analytic functions. Data-driven strategic decisions are made using online analytical processing (OLAP) based on machine learning and data analytics cognitive web services. The key variance between the two approaches to prediction is that linear regression always measures a single weight of each pupil, and local weights linear regression calculates the weight independently of each learner to predict the exact score. The content collected by the portfolio may involve different activities or works that learners have done during the curriculum, like homework or written reports, video, audio taps of different learning activities. To effectively expose the learning process, outcomes, and progress of the learners completely evaluated using student scores with the proposed SWISM method. Figure 7 shows the score analysis using the proposed SWISM method.

### Prediction Ratio

This paper presents the two prediction approaches with regression analysis of score prediction known as local weights linear regression and linear regression. The major variance between the two prediction approaches is that linear regression estimates a single weight value for every student. Local weights linear regression determines the weight value independently that matches every learner's outcomes to predict the accurate score. An analysis of technical evidence leads us to believe that standardized student test scores are one piece of information school leaders can use to make teacher effectiveness judgments. The tests show that the proposed cloud analytical model SWISM offers intelligent learning recommendations, student preference prediction, and learning efficiency. Analytic functions for data storage and data warehouses will soon be included in database systems in the future. Cognitive web services for machine learning and data analytics make data-driven strategic decisions. Any sound appraisal will inevitably require a balance of several variables and provide a more precise view of what teachers do in the classroom and how this helps student learning.

Figure 7. Score Analysis



Moreover, every recognized model will alter the weights to create the predicted score interval accurately. Figure 8 shows the prediction ratio using the proposed SWISM approach. An interaction between a human and a software programme is called interactivity in computing. It's not hypertext on the Web that can be interactive; many non-Web applications on any computer system provide this functionality.

### Students Satisfaction Ratio

Student satisfaction is a significant parameter of the learning experiences quality. The linear regression analysis has been executed to identify the contribution of predictor attributes to student satisfaction. The outcomes demonstrated that teachers-learner interaction, student-content interaction, and Internet automaticity were strong student satisfaction predictors and student-self-regulated interactions help students. The relationship between learner-content indicates the greatest difference in the satisfaction of students. The tests show that the cloud analytical model SWISM provides intelligent recommendations, student preference prediction and efficiency in learning. In the future, database systems will include analytic functions for data storage and data warehouses, as well. Data-driven strategic decisions are made using cognitive web services for machine learning and data analytics. In addition, gender, class, and time spent online each week tended to affect student-learner experiences, Internet self-efficacy, and self-regulation. The artificial intelligence-based proposed SWISM method enhances the student's satisfaction compared to other existing approaches. Figure 9 demonstrates the student's satisfaction ratio using the proposed SWISM method.

The proposed Smart Web-based Interactive System Modeling (SWISM) based on artificial intelligence in teaching and learning for students achieves high interaction of 93.4%, learning performance of 94.2%, satisfaction of 97.5%, prediction ratio of 96.9% when compared to other exiting Artificial intelligence in education(AIED), artificial neural networks (ANN), artificial bee colony (ABC) methods in cognitive web services for machine learning and data analytics.

## CONCLUSION

This paper presents the Smart Web-based Interactive System Modeling (SWISM) based on artificial intelligence in teaching and learning for students. Web-based or online, or E-Learning environment plays an important role in the modern education system. Learning materials are available in various

Figure 8. Prediction Ratio

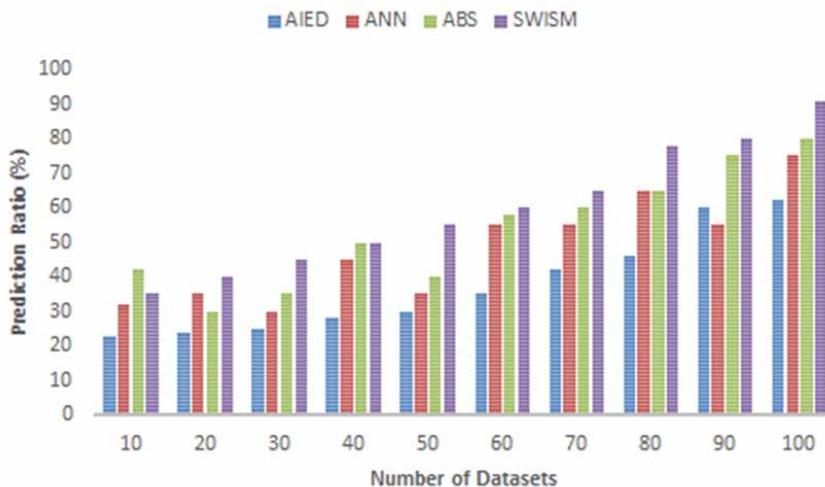
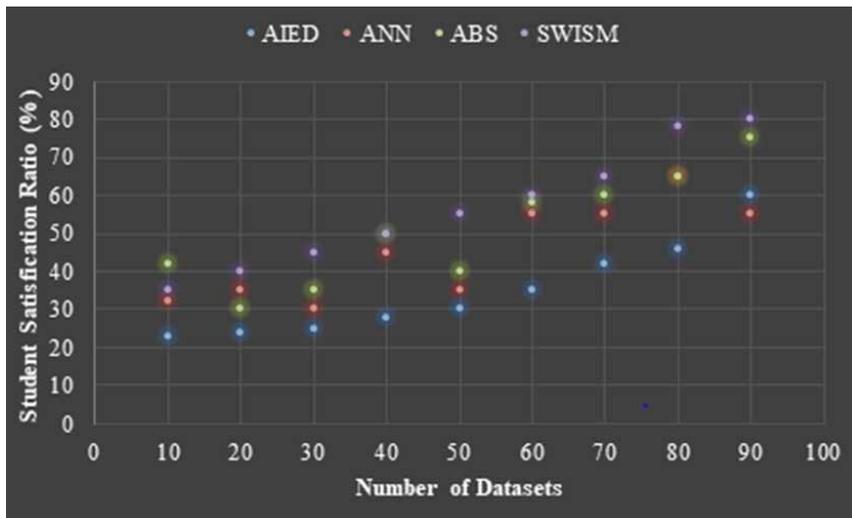


Figure 9. Students Satisfaction ratio



formats; enabling personalized learning objects is a significant characteristic of the modern learning management system. The proposed system utilizes an ML algorithm and regression exploration based on the physiological data, interaction outcomes, and study students' performance in real-time. The lack of data control, ambiguity, and data comprehension hinder effective solutions development and deployment because of the demand for adaptability and customization in AI-based learning programs in cognitive web services for machine learning and data analytics. This made teachers adjust the teaching process and improve students' learning efficiency. The findings revealed that the participants noticed web-based planning, instruction, and self-reflection feedback for their education. The desire to look at themselves from the viewpoint of their students and to reflect on such instructional and learning problems allowed them to accurately and efficiently evaluate their teaching. The experimental results show that the proposed SWISM method achieves high interaction, learning performance, satisfaction, and prediction ratio compared to other existing methods in cognitive web services for machine learning and data analytics.

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*Velliangiri.S obtained his Bachelor's in Computer Science and Engineering from Anna University, Chennai. Master's in Computer Science and Engineering from karpagam University, Coimbatore and Doctor of Philosophy in Information and Communication Engineering from Anna University, Chennai. Currently, he is working as an Associate Professor in CMR Institute of Technology, Hyderabad, Telangana. He was a member of the Institute of Electrical and Electronics Engineers (IEEE) and International Association of Engineers (IAENG). He is specialized in Network security and Optimization techniques. He published ten International journals and presented five International conferences. He was the reviewer of Springer, Inderscience and reputed Scopus indexed journals.*