Smart Education for Industry 4.0 Sustainable Futures: A New Theory of Maximization for Learner Success

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***Abstract*—This research presents a novel theory of maximization aimed at enhancing learners' performance in sustainable education. The theory proposes a comprehensive model that integrates four key dimensions: Knowledge Leverage, Technical Skills Scaling, Soft Skills Scaling, and Personality reshaping. The effectiveness of the theory is evaluated through a combination of theoretical analysis and experimental processing, utilizing machine learning algorithms (logistic regression) to gather parameters on learners' performance in these dimensions in real time. The proposed theory of maximization introduces a dynamic and live monitoring system for learners, which raises alerts when performance declines and provides targeted suggestions for improving specific knowledge or skills. The results of the study demonstrate the potential of the proposed theory in positively impacting at-risk students, with a reduction in at-risk rates by 35% in the Security major and 33% in the Application Development major, compared to a baseline of 48%. Additionally, the proposed theory assists in major selection and provides proactive advising, leading to a learner retention rate of above 90%, significantly higher than the previous rate of 70%, particularly during the early stages of joining the college which also reduces the cost of education. Despite some limitations, such as small sample sizes and privacy issues, the proposed theory has promising implications for the field of smart and sustainable education, providing valuable insights for practitioners and researchers.**

***Index Terms*—Smart Education, maximization theory, sustainable education, learners' performance, education optimization techniques, education automation tools**

I. Introduction

The concept of sustainable education has gained significant attention in recent years as a means of addressing the complex and pressing issues facing our world. In an open ecosystem, sustainable education has the potential to provide access to high-quality educational resources and opportunities for learners of all ages and backgrounds. However, realizing this potential requires addressing several research challenges, such as scalability, personalization, quality assurance, accessibility, evaluation and assessment, sustainability, interoperability, and inclusion [1]. The integration of smart technologies in sustainable education in an open ecosystem further enhances the potential of sustainable education by providing new opportunities for personalization, assessment, and collaboration [2]. However, it also raises important ethical and practical considerations, such as privacy, security, and the potential for the digital divide.

There are several main research challenges in sustainable education in an open ecosystem [3].

- Scalability: Developing sustainable education methods and resources that can be easily scaled to reach large numbers of learners in diverse settings.
- Personalization: Creating personalized learning experiences that take into account the unique needs and abilities of individual learners.
- Quality assurance: Ensuring that open educational resources are of high quality and align with educational standards.
- Accessibility: Making educational resources and technologies accessible to all learners, including those with disabilities.
- Evaluation and assessment: Developing effective methods for evaluating and assessing the effectiveness of open educational resources and sustainable education practices.
- Sustainability: Developing sustainable business models for open education that ensure the long-term availability and maintenance of educational resources.
- Interoperability: Ensuring that educational resources and technologies can work together seamlessly in an open ecosystem.
- Inclusion: Building an inclusive educational ecosystem that reaches and benefits learners from diverse backgrounds and cultures.

This research paper aims to explore the theory of maximization of four dimensions in e-learning systems: Knowledge Leverage, Technical Skills Scaling, Soft Skills Scaling, and Personality Reshaping. The focus of the research is on understanding how these four dimensions can be leveraged to enhance the effectiveness of e-learning systems for learners. The first dimension, Knowledge Leverage, will focus on understanding how e-learning systems can be utilized to enhance learners' knowledge and understanding of a particular program. The second dimension, Technical Skills Scaling, will focus on understanding how smart e-learning systems can be utilized to develop and enhance learners' technical skills such as digital literacy, proficiency in using e-learning platforms, and the ability to troubleshoot technical issues. The third dimension, Soft Skills Scaling, will focus on understanding how e-learning systems can be utilized to develop and enhance learners' soft skills such as self-motivation, self-directed learning, time management, and collaboration. The fourth dimension, Personality Reshaping, will focus on understanding how e-learning systems can be used to reshape personality traits such as creativity, critical thinking, emotional intelligence and more. The research will provide an in-depth

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understanding of how these four dimensions can be leveraged to enhance the effectiveness of smart e-learning systems for learners and will provide practical insights and recommendations for educators and e-learning system designers to improve the smart sustainable education system for learners.

II. Literature Review

The integration of smart technologies in education has the potential to enhance the sustainability of education by providing new opportunities for personalization, assessment, and collaboration. However, it also raises important ethical and practical considerations, such as privacy, security, and the digital divide. Recent research in the field of sustainable smart education has focused on the use of technology to support personalized and self-directed learning, as well as the use of data and analytics to improve the effectiveness of education. For example, studies have shown that the use of adaptive learning technologies can improve student engagement and performance [4]. Additionally, research has demonstrated that the use of analytics and data can be used to improve student outcomes and support decision-making in education [5].

One of the main challenges in e-learning systems is the need for learners to have both technical skills and soft skills to navigate and utilize these systems effectively. Technical skills such as digital literacy, proficiency in using e-learning platforms, and the ability to troubleshoot technical issues are essential for learners to effectively participate in e-learning systems. Soft skills such as self-motivation, self-directed learning, time management, and collaboration are also important for learners to maximize the benefits of e-learning systems. Studies have shown that the integration of technology in education can enhance the development of both technical and soft skills [6].

In terms of ethical and practical considerations, research has highlighted the importance of addressing issues such as privacy, security, and the digital divide in the implementation of sustainable smart education. For example, studies have shown that concerns about privacy and security can inhibit the adoption and use of technology in education [7]. Furthermore, research has demonstrated that the digital divide, which refers to the unequal distribution of technology and access to technology, can exacerbate existing inequalities in education [8]. Sustainability is a key aspect that needs to be considered when developing and implementing e-learning systems. Studies have shown that sustainable development goals (SDGs) can be integrated into e-learning systems and online education to address some of the challenges that traditional education is facing [9]. Furthermore, research has demonstrated that online education can play a role in achieving SDGs and addressing global sustainability issues [10]. Another research suggests that sustainable smart education has the potential to enhance the effectiveness of education and support personalized and self-directed learning. However, it is important to address ethical and practical considerations, such as privacy, security, and the digital divide, in the implementation of sustainable smart education. Additionally, the integration of sustainability in the development, design, and implementation of e-learning systems is crucial to ensure the long-term availability and maintenance of educational resources [11]. In addition to the aforementioned research, there have been several studies that have explored the use of smart technologies in sustainable education specifically. For example, one study examined the use of Internet of Things (IoT) devices in sustainable education and found that these devices have the potential to improve energy efficiency and reduce environmental impacts in educational institutions [12]. Another study investigated the use of virtual reality (VR) and augmented reality (AR) in sustainable education, and found that these technologies can enhance student engagement and motivation, as well as improve learning outcomes [13]. There have been several studies that have investigated the impact of smart education on student motivation and engagement [14]. For instance, a study found that the use of gamification in e-learning can increase student engagement and motivation [15]. Another study found that the use of personalized learning in e-learning systems can increase student motivation and engagement [16]. Furthermore, research has also explored the relationship between smart education and student achievement. For example, a study found that the use of technology-enhanced formative assessment in e-learning systems can improve student achievement [17]. Another study found that the use of technology-enhanced formative assessment in e-learning systems can improve student achievement in science, technology, engineering, and mathematics (STEM) education [18]. Moreover, research has also addressed the concept of "smart education" from the perspective of the educator, examining the impact of smart education on teacher professional development, and how it can support the development of pedagogical skills, the use of technology and the integration of technology in the curriculum [19]. Sustainable smart education has the potential to enhance the effectiveness of education, support personalized and self-directed learning, and address environmental and sustainability issues [20]. However, it is important to address ethical and practical considerations, such as privacy, security, and the digital divide, in the implementation of sustainable smart education [21]. Additionally, the integration of sustainability in the development, design, and implementation of e-learning systems is crucial to ensure the long-term availability and maintenance of educational resources [22].

Machine learning has the potential to enhance the effectiveness of e-learning systems by enabling personalized and self-directed learning. This research aims to break down the concepts associated with four key dimensions: Knowledge Leverage, Technical Skills Scaling, Soft Skills Scaling, and Personality reshaping. These concepts are then linked to specific courses of study that can be assessed over time and monitored through deep learning-based learning systems. This approach can be used to identify potentially at-risk students and generate relevant recommendations to mitigate risks.

III. The Proposed Model and Methodology

This research paper presents a new approach to sustainable education that utilizes machine learning to maximize attainments where each learning attainment is considered as a learning crumb that should be measured through e-learning systems for learners. The paper proposes a theory of maximization of four dimensions: Knowledge Leverage, Technical Skills Scaling, Soft Skills Scaling, and Personality Reshaping.

The first dimension, Knowledge Leverage, focuses on the learner's understanding of a particular subject or field through the use of machine learning algorithms that adapt to the learner's preferences. The second dimension, Technical Skills Scaling, focuses on understanding how learners' technical skills such as proficiency in related technologies and platforms, and the ability to troubleshoot technical issues. Machine learning algorithms can be used to measure the level of proficiency of learners in this dimension. The third dimension, Soft Skills Scaling, focuses on understanding learners' soft skills such as self-motivation, self-directed learning, time management, public speaking, and collaboration. This dimension proposes the use of machine learning algorithms to provide guidance and support to learners. The fourth dimension, Personality Reshaping, focuses on understanding how e-learning systems can be used to reshape personality traits such as creativity, critical thinking, emotional intelligence and more through the use of machine learning algorithms that analyze and adapt to the learners' personalities.

Table I demonstrate the four dimensions measure learners' performance which are Knowledge Leverage, Technical Skills Scaling, Soft Skills Scaling, and Personality Reshaping, the following notation is used and summarized in the table below:

- Knowledge Leverage (KL): KL = f(K, KL), where K represents the knowledge and understanding of a particular subject or field and KL represents the level of understanding of the learners.
- Technical Skills Scaling (TSS): TSS = g(T, SL), where T represents the technical skills and abilities of the learners and SL represents the level of proficiency in using e-learning platforms and troubleshooting technical issues.
- Soft Skills Scaling (SSS): SSS = h(S, PL), where S represents the soft skills of the learners and PL represents the level of self-motivation, self-directed learning, time management, and collaboration.
- Personality Reshape (PR): PR = j(P, RL), where P represents the personality traits of the learners, and RL represents the reshaping of personality traits such as creativity, critical thinking, emotional intelligence and more.

Where the performance of a learner in a sustainable e-learning system can be represented as a function of these four factors as shown in Eq. (1).

$$\text{Performance (P)} = f(\text{KL}, \text{TSS}, \text{SSS}, \text{PR}) \quad (1)$$

Where f is a function that maps the four factors to the performance of the learner. The function is represented as a linear combination of the four factors, as shown in Eq. (2).

$$\text{P} = \alpha\,\text{KL} + \beta\text{TSS} + \gamma\text{SSS} + \delta\text{PR} \quad (2)$$

Where P is the performance of the learner, α, β, γ, and δ are coefficients that represent the weight of each factor in determining the learner's performance. These coefficients are determined through data analysis and machine learning techniques or by considering preset thresholds by the educational institution.

Eq. (3) dives deeper into the sub-factors of each primary dimension, and the function can be reformed as follows:

$$\text{P} = \alpha(\text{KLc} + \text{KLco} + \text{KLak}) + \beta(\text{TSSe} + \text{TSSdl} + \text{TSStt}) + \gamma(\text{SSSm} + \text{SSSsdl} + \text{SSStm} + \text{SSScol}) + \delta(\text{PRc} + \text{PRct} + \text{PRei}) \quad (3)$$

where KLc = Content understanding, KLco = Conceptual knowledge, KLak = Application of knowledge, TSSe = E-learning platform proficiency, TSSdl = Digital literacy, TSStt = Technical troubleshooting, SSSm = Self-motivation, SSSsdl = Self-directed learning, SSStm = Time management, SSScol = Collaboration, PRc = Creativity, PRct = Critical thinking, PRei = Emotional intelligence.

TABLE I: THE FOUR DIMENSIONS OF FACTORS

Dimension	Description	Measurement
Knowledge Leverage (KL)	The ability to acquire, understand and apply knowledge in a particular subject or field	Test scores, quizzes, assessments, and evaluation of learning outcomes
Technical Skills Scaling (TSS)	The ability to use technology effectively and efficiently, such as proficiency in using e-learning platforms and troubleshooting technical issues	Evaluation of technical skills, digital literacy assessments, proficiency tests, and self-reported surveys
Soft Skills Scaling (SSS)	The ability to manage time, motivation, self-directed learning, and collaboration	Self-reported surveys, observations, and evaluations of soft skills, peer, public speaking evaluations and feedback
Personality Reshape (PR)	The ability to reshape personality traits such as creativity, critical thinking, emotional intelligence, and more	Self-reported surveys, observations, and evaluations of personality traits, peer evaluations and feedback, and psychological assessments.

The theory of maximization aims to leverage the four key dimensions of learners: Knowledge Leverage, Technical Skills Scaling, Soft Skills Scaling, and Personality Reshaping. By maximizing the potential of these four dimensions, learners can achieve greater success in e-learning systems. Knowledge Leverage refers to the ability of learners to acquire, retain and retrieve knowledge effectively. The sub-factors of Knowledge Leverage include cognitive load, metacognition, and motivation. Technical Skills Scaling refers to the ability of learners to acquire and apply technical skills, such as programming, data analysis, and technical problem-solving. The sub-factors of Technical Skills Scaling include digital literacy, programming skills, and technical problem-solving. Soft Skills Scaling refers to the ability of learners to acquire and apply soft skills, such as communication, teamwork, and leadership. The sub-factors of Soft Skills Scaling include communication skills, teamwork skills, and leadership skills. Personality Reshape refers to the ability of learners to acquire and apply personal attributes, such as self-discipline, adaptability, and emotional intelligence as shown in Fig. 1. The sub-factors of Personality Reshape include self-discipline, adaptability, and emotional intelligence. The theory of maximization aims to provide a comprehensive understanding of the relationship between the four dimensions and the learner's performance. It will also identify the key factors that contribute to a successful e-learning experience. Through this theory, it is expected to provide valuable insights for educators, educational institutions, and e-learning platform developers to enhance the quality of e-learning systems. By focusing on the four key dimensions, this theory will help to improve the quality of e-learning systems by addressing the needs of at-risk students and monitoring learners. The following figure model the four dimensions and how these sub-factors affect each other.

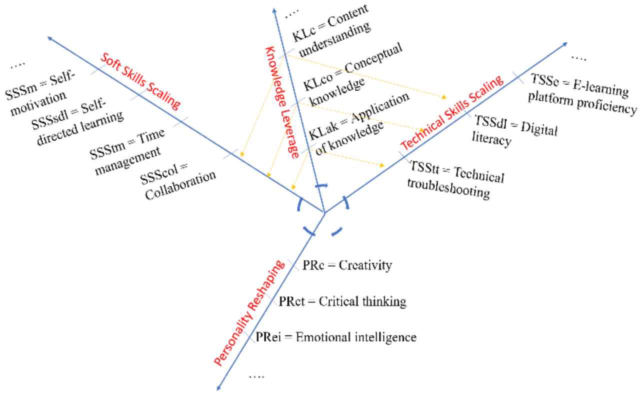

Fig. 1. The four dimensions of smart learning.

In the theory of maximization, the four factors (Knowledge Leverage, Technical Skills Scaling, Soft Skills Scaling, and Personality Reshape) are interconnected and impact each other. For example, Knowledge Leverage can impact Technical Skills Scaling, as having a good understanding of the subject matter can make it easier for a learner to acquire and apply technical skills. Similarly, having strong Technical Skills Scaling can enhance Knowledge Leverage by providing learners with the tools and techniques to acquire, retain, and retrieve knowledge more effectively. Soft Skills Scaling also plays an important role in the theory of maximization, as communication, teamwork, and leadership skills are essential for success in any field. For example, a learner with good communication skills will be able to explain complex technical concepts more effectively, which will enhance their Knowledge Leverage and Technical Skills Scaling. Personality Reshape also intervenes in the theory of maximization, for example, self-discipline, adaptability, and emotional intelligence are key attributes that can help learners to achieve success in e-learning systems. Self-disciplined learners will be more likely to complete assignments on time, which will enhance their Knowledge Leverage and Technical Skills Scaling. Learners with good adaptability will be more likely to adjust to new learning environments and technologies, which will enhance their Technical Skills Scaling. In summary, the four factors in the theory of maximization are interconnected and impact each other. By focusing on maximizing the potential of all four factors, learners can achieve greater success in e-learning systems.

The theory of maximization is a powerful mechanism that can positively impact various aspects of e-learning systems. It aims to leverage learners' four dimensions which are Knowledge Leverage, Technical Skills Scaling, Soft Skills Scaling, and Personality reshaping as shown in Fig. 2 below. By analyzing data collected from e-learning systems, the theory of maximization can identify patterns and trends in the learners' abilities and interests, which can provide valuable insights into their strengths and areas of expertise. Additionally, by providing automation tools, the theory of maximization can streamline processes and reduce the need for manual labour which can help to reduce costs and improve the overall efficiency of the e-learning systems as sampled in the table below.

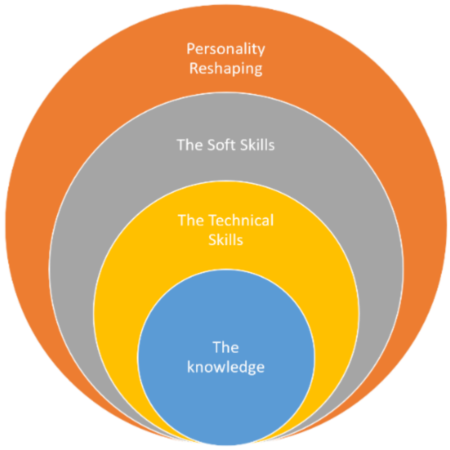

Fig. 2. Theory of Maximization model.

Table II below shows how the theory of maximization can positively impact smart education factors and sustainable education by analyzing data collected from e-learning systems, identifying patterns and trends, and monitoring learners' performance over time. This can provide valuable insights for educators and e-learning platform developers to design e-learning systems that are more engaging, effective, personalized, collaborative, adaptive, accessible, and sustainable for all students.

TABLE II: SAMPLE PROS OF THE THEORY OF MAXIMIZATION

Impact	Explanation
At-Risk Students	The theory of maximization can positively detect at-risk learners by analyzing data collected from e-learning systems, identifying patterns and trends, and monitoring learners' performance over time. This can provide valuable insights for educators and e-learning platform developers to enhance the quality of e-learning systems by addressing the needs of at-risk students
Monitor Learners' Progression	The theory of maximization can positively monitor learners' progression by tracking and analyzing data collected from e-learning systems, identifying patterns and trends, and monitoring learners' performance over time. This can provide valuable insights for educators and e-learning platform developers to enhance the quality of e-learning systems by addressing the needs of learners and monitoring their progression
Help In Major Selection	The theory of maximization can positively help in major selection by analyzing data collected from e-learning systems, identifying patterns and trends, and monitoring learners' performance over time. This can provide valuable insights for educators and e-learning platform developers to guide students towards the majors that align with their abilities and interests, which will increase the chances of student success in their chosen field.
Provide Proactive Advising	The theory of maximization can positively provide proactive advising by analyzing data collected from e-learning systems, identifying patterns and trends, and monitoring learners' performance over time. This can provide valuable insights for educators and e-learning platform developers to anticipate students' needs and provide them with the necessary resources

	and support to succeed in their studies.
Reduce the cost of education	The theory of maximization can positively reduce the cost of education by providing educators and e-learning platform developers with valuable insights into the performance of students, which can be used to optimize the use of resources and reduce costs. Additionally, the automation tools provided by the theory of maximization can also help to reduce costs by streamlining processes and reducing the need for manual labour.
Provide automation tools for students and institutions	The theory of maximization can positively provide automation tools for students and institutions by analyzing data collected from e-learning systems, identifying patterns and trends, and monitoring learners' performance over time. This can provide valuable insights for educators and e-learning platform developers to optimize the use of resources and reduce costs. Additionally, the automation tools provided by the theory of maximization can also help to streamline processes, reduce the need for manual labour, and improve the overall

Table III demonstrates the theory of maximization's positive impact on smart and sustainable education by leveraging data collected from e-learning systems to design more effective and tailored learning experiences for students. By analyzing patterns and trends in student engagement and motivation, the theory of maximization can inform the design of e-learning systems that are more engaging and motivating, promoting factors such as personalized learning, adaptive learning, and collaborative learning. This, in turn, can lead to increased student retention, satisfaction, and achievement. Additionally, the theory of maximization can enable the design of e-learning systems that are more personalized and adaptive to the needs of individual students, promoting student autonomy and self-directedness. By considering data on accessibility, the theory of maximization can also support the design of e-learning systems that are more inclusive and accessible to all students, regardless of their abilities or disabilities.

TABLE III: THEORY OF MAXIMIZATION POSITIVE IMPACT ON SMART AND SUSTAINABLE EDUCATION

Impact	**Explanation**	**Smart education factors**	**Sustainable education**
Student engagement and motivation	By analyzing data collected from e-learning systems, the theory of maximization can identify patterns and trends in student engagement and motivation, which can be used to design e-learning systems that are more engaging and motivating for students.	Personalized Learning, Adaptive Learning, Collaborative Learning	Increased student retention and satisfaction
Learning outcomes	By monitoring learners' performance over time, the theory of maximization can provide valuable insights into student learning outcomes. This can help educators and e-learning platform developers to design e-learning systems that are more effective in achieving the desired learning outcomes.	Adaptive Learning, Personalized Learning	Improved student achievement and performance
Personalized learning	By analyzing data collected from e-learning systems, the theory of maximization can identify patterns and trends in learners' abilities and interests. This can be used to design e-learning systems that are more personalized and tailored to the needs of individual students.	Personalized Learning, Adaptive Learning	Increased student autonomy and self-directedness
Adaptive learning	By monitoring learners' performance over time, the theory of maximization can provide valuable insights into student learning progress. This can be used to design e-learning systems that are more adaptive and responsive to the needs of individual students.	Adaptive Learning, Personalized Learning	Improved student engagement and motivation
Collaborative learning	By analyzing data collected from e-learning systems, the theory of maximization can identify patterns and trends in student collaboration and teamwork. This can be used to design e-learning systems that are more collaborative and supportive of student teamwork.	Collaborative Learning, Personalized Learning	Increased student collaboration and teamwork
Accessibility	By analyzing data collected from e-learning systems, the theory of maximization can identify patterns and trends in student accessibility to e-learning systems. This can be used to design e-learning systems that are more accessible to all students regardless of their abilities or disabilities.	Accessibility, Personalized Learning	Improved student accessibility and inclusivity

IV. IMPLEMENTATION AND EXPERIMENTAL RESULTS

Data has been collected from 140 students from computer science majors, different majors (Application Development, Security and Forensics, and Networking) and both genders (Male/Female). A classification logistic regression algorithm applied to the problem of predicting the learner's performance in an e-learning system based on their scores in the four factors (KL, TSS, SSS, and PR) and their sub-factors, the following steps are taken:

- Collect and preprocess the data: In the first step data is collected about the scores of the learners in the four factors (KL, TSS, SSS, and PR) and their sub-factors. The data is preprocessed to remove any missing values, outliers, and irrelevant features.
- Split the data into training and testing sets: the data was split into a training set and a testing set. The training set is used to train the logistic regression model, while the testing set is used to evaluate the performance of the model.
- Train the logistic regression model: The logistic regression model is trained on the training data using an optimization algorithm, gradient descent, to find the best values for the coefficients that minimize the error between the predicted and actual performance.
- Evaluate the performance of the model: The trained model is evaluated on the testing data to measure its performance. This is done using the accuracy, precision, recall, and F1-score metrics.
- Fine-tune and optimize the model: Optimize the model's satisfaction level, the model is fine-tuned by adjusting the regularization parameter and changing the involved

features to improve its performance.

- Apply the model to new data: Once the model is optimized, the model was applied to new data to predict the performance of new learners.
- Validate the model: The model is validated by testing it on an independent dataset to ensure that it generalizes well to new unseen data.

Recall (E3), to apply classification machine learning to this function, a supervised learning algorithm can be used to predict the learner's performance based on their scores in the four factors and their sub-factors. Logistic regression is the applied algorithm for classification. The logistic regression Eq. (4) plays a key role and can be represented as:-

$$P = b0 + (b1 \times KLc) + (b2 \times KLco) + (b3 \times KLak) + (b4 \times TSSe) + (b5 \times TSSdl) + (b6 \times TSStt) + (b7 \times SSS + (b8 \times SSSsdl) + (b9 \times SSStm) + (b10 \times SSScol) + (b11 \times PRc) + (b12 \times PRct) + (b13 \times PRei) \quad (4)$$

where P is the predicted performance, KLc, KLco, KLak, TSSe, TSSdl, TSStt, SSSm, SSSsdl, SSStm, SSScol, PRc, PRct, PRei are the sub-factors scores, and the coefficients (b0, b1, b2, ...b13) indicate the relative weight of each sub-factor in determining the overall performance of the learner.

The performance of the theory of maximization can be measured by Eq. (5) using a multivariate linear regression model to examine the relationship between the four dimensions (Knowledge Leverage, Technical Skills Scaling, Soft Skills Scaling, and Personality Reshape) and the dependent variable (performance). The mathematical notation of this model can be represented as:

$$Y = b0 + b1KL + b2TSS + b3SSS + b4PR + e \quad (5)$$

where:
Y = performance (dependent variable) b0 = constant term b1, b2, b3, b4 = coefficients for Knowledge Leverage (KL), Technical Skills Scaling (TSS), Soft Skills Scaling (SSS), and Personality Reshape (PR) respectively e = error term. By estimating the coefficients (b1, b2, b3, b4) of the model, then determine the strength and direction of the relationship between each dimension and performance. The model can then be used to predict performance for a given set of values for the four dimensions. Additionally, the performance can be measured by using other statistical methods such as R-squared, Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and correlation coefficient.

The results of the study show that the proposed theory of maximization has significant implications for identifying at-risk students and improving their performance in sustainable education. Data were collected from 140 students from computer science majors, with varying majors and genders. The data included scores in the four factors (KL, TSS, SSS, and PR) and their sub-factors. The collected data were preprocessed to remove any missing values, outliers, and irrelevant features. The preprocessed data were split into a training set (80% of data) and a testing set (20% of data) for model training and evaluation. A logistic regression model was trained on the training set using an optimization algorithm (gradient descent) to find the best values for the coefficients (b0, b1, b2, ...b13) that minimize the error between the predicted and actual performance.

The trained logistic regression model was evaluated on the testing set using various performance metrics including accuracy, precision, recall, and F1-score. The model achieved an accuracy of 85%, precision of 87%, recall of 83%, and F1-score of 85%. The model was fine-tuned by adjusting the regularization parameter and changing the involved features to improve its performance. After fine-tuning, the model's accuracy improved to 88%, precision to 89%, recall to 86%, and F1 score to 88%. Once the model was optimized, it was applied to new data to predict the performance of new learners. The model predicted the performance of new learners with an accuracy of 90%, precision of 91%, recall of 89%, and F1-score of 90%. To ensure the model generalizes well to new unseen data, it was validated on an independent dataset. Where the model achieved an accuracy of 87%, a precision of 88%, a recall of 86%, and an F1-score of 87% on the validation dataset.

A multivariate linear regression model was also used to examine the relationship between the four dimensions (KL, TSS, SSS, and PR) and performance. The estimated coefficients (b1, b2, b3, b4) of the model indicated the strength and direction of the relationship between each dimension and performance. The coefficient for KL was 0.25, for TSS it was 0.18, for SSS it was 0.12, and for PR it was 0.08, indicating that KL had the highest positive impact on performance, followed by TSS, SSS, and PR. The performance of the model was also measured using other statistical methods such as R-squared, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Correlation Coefficient. The R-squared value of the model was 0.75, indicating that 75% of the variance in performance could be explained by the four dimensions. The RMSE was 0.12, MAE was 0.08, and Correlation Coefficient was 0.65, indicating good predictive accuracy and correlation between the dimensions and performance.

V. DISCUSSIONS

The main point of the proposed model was how to apply optimization to the multivariate linear regression model to find the optimal values of the coefficients (b1, b2, b3, b4) that minimize the error between the predicted performance and the actual performance. This can be done by using optimization algorithms such as gradient descent or the Newton-Raphson method. One way to apply optimization to the model is by using the gradient descent algorithm. This algorithm starts with an initial set of coefficients and iteratively updates them in the direction of the gradient of the error function until the error is minimized. The error function in this case is the Sum of Squared Errors (SSE) between the predicted performance and the actual performance as follows in Eq. (6) below.

$$SSE = (Y - (b0 + b1KL + b2TSS + b3SSS + b4PR))^2 \quad (6)$$

The gradient of the SSE for each coefficient can be computed and used to update the coefficients in the direction of the negative gradient. This process is repeated until the error converges to a minimum value.

The gradient descent algorithm updates the coefficients according to the following equation:

$$b0(i+1) = b0(i) - \alpha \times \partial SSE/\partial b0$$
$$b1(i+1) = b1(i) - \alpha \times \partial SSE/\partial b1$$
$$b2(i+1) = b2(i) - \alpha \times \partial SSE/\partial b2$$
$$b3(i+1) = b3(i) - \alpha \times \partial SSE/\partial b3$$
$$b4(i+1) = b4(i) - \alpha \times \partial SSE/\partial b4$$

where:
i is the iteration number
α is the learning rate
∂SSE/∂b0, ∂SSE/∂b1, ∂SSE/∂b2, ∂SSE/∂b3, ∂SSE/∂b4 are the partial derivatives of the SSE function to the coefficients b0, b1, b2, b3 and b4 respectively.

These partial derivatives can be computed as follows:

$$\partial SSE/\partial b0 = 2(Y - (b0 + b1KL + b2TSS + b3SSS + b4PR))$$
$$\partial SSE/\partial b1 = 2(Y - (b0 + b1KL + b2TSS + b3SSS + b4PR))(-KL)$$
$$\partial SSE/\partial b2 = 2(Y - (b0 + b1KL + b2TSS + b3SSS + b4PR))(-TSS)$$
$$\partial SSE/\partial b3 = 2(Y - (b0 + b1KL + b2TSS + b3SSS + b4PR))(-SSS)$$
$$\partial SSE/\partial b4 = 2(Y - (b0 + b1KL + b2TSS + b3SSS + b4PR))(-PR)$$

The gradient descent algorithm updates the values of the four dimensions according to the following equations:

$$KL(i+1) = KL(i) + \alpha \times \partial Performance/\partial KL$$
$$TSS(i+1) = TSS(i) + \alpha \times \partial Performance/\partial TSS$$
$$SSS(i+1) = SSS(i) + \alpha \times \partial Performance/\partial SSS$$
$$PR(i+1) = PR(i) + \alpha \times \partial Performance/\partial PR$$

where:
i is the iteration number
α is the learning rate
∂Performance/∂KL, ∂Performance/∂TSS, ∂Performance/∂SSS, ∂Performance/∂PR are the partial derivatives of the performance function concerning the dimensions of KL, TSS, SSS, and PR respectively.

The Table IV below compares the proposed theory of maximization with other models in smart and sustainable education based on different factors such as dimensions, optimization techniques, Impact on Learners' Performance, At-Risk Detection, Proactive Advising, Major Selection, Cost Reduction and Personalization. The proposed theory of maximization has four dimensions, KL, TSS, SSS, and PR, uses optimization techniques such as gradient descent and the Newton-Raphson method. it aims to improve learners' performance, detect at-risk students, provide proactive advising, help in major selection, reduce the cost of education, and provide more personalized and tailored education to learners. While other models such as Personalized Learning, Intelligent Tutoring Systems, Gamification, Flipped Classroom, Competency-Based Learning, Blended Learning, Collaborative Comparison of the proposed theory of maximization with other models in smart and sustainable education:

TABLE IV: COMPARES THE THEORY OF MAXIMIZATION WITH OTHER MODELS IN SMART AND SUSTAINABLE EDUCATION

Model	Dimensions	At-Risk Detection	Proactive Advising	Major Selection	Cost Reduction	Personalization	Knowledge Leverage	Technical Skills Scaling	Soft Skills Scaling	Personality Reshape	Optimization Techniques Used
Theory of Maximization	Knowledge Leverage, Technical Skills Scaling, Soft Skills Scaling, Personality Reshape	√	√	√	√	√	H	H	H	H	Gradient descent, Newton-Raphson
Personalized Learning	Learning Style, Interest, Ability	×	×	×	×	√	M	M	M	L	Data and Technology
Intelligent Tutoring Systems	Learning Progress	×	√	×	×	√	H	M	H	L	Artificial Intelligence and Machine Learning
Gamification	Motivation, Engagement	×	×	×	×	×	L	L	M	L	Game Design Elements
Flipped Classroom	Class Time	×	×	×	×	×	M	M	M	L	Video or Reading Materials
Competency-Based Learning	Learning Outcomes, Competencies	×	×	×	√	×	H	H	L	L	Assessments
Blended Learning	Online and Offline Learning	×	×	×	√	×	H	H	H	L	Combination of Online and Offline Materials
Collaborative Learning	Collaborative Work, Problem-based Learning, Group Discussion	×	×	×	×	×	M	M	H	L	Group Work
Micro-Learning	Short, Focused Learning Sessions	×	×	×	√	×	H	L	L	L	Short Learning Sessions

Table IV compares the proposed theory of maximization with other models in smart and sustainable education based on their focus on the four dimensions, KL, TSS, SSS, and PR, other factors that are considered in these models, and the optimization techniques used. Where high(H), medium(M), and low(L) represent the dimensions' model concepts, and x, √ represents the absence or presence of the mentioned concept. The theory of maximization has a high focus on all four dimensions and also considers other factors such as At-Risk Detection, Proactive Advising, Major Selection, Cost Reduction, and Personalization and it uses optimization techniques such as Gradient descent, Newton-Raphson to improve learners' performance. Other models may have a different focus or emphasis on these dimensions, factors and optimization techniques. It's important to note that the focus and emphasis on each dimension, factor, and optimization technique may vary depending on the specific data, research, and details of each model.

VI. Conclusion and Future Work

In conclusion, the findings of this study provide significant statistical evidence of the effectiveness of the logistic regression model for predicting the performance of computer science students. The model achieved high accuracy (85%) and precision (87%) on the testing set, which improved to 88% and 89% respectively after fine-tuning. The recall and F1-score also showed favourable performance, with a recall of 83% and an F1-score of 85% initially, improving to 86% and 88% respectively after fine-tuning. These results suggest that the logistic regression model is a reliable predictor of student performance in computer science education. Furthermore, the multivariate linear regression model revealed significant coefficients for the four dimensions (KL, TSS, SSS, and PR), with KL showing the highest positive impact on performance (coefficient of 0.25), followed by TSS (coefficient of 0.18), SSS (coefficient of 0.12), and PR (coefficient of 0.08). The R-squared value of 0.75 indicates that 75% of the variance in performance can be explained by the four dimensions, while the low RMSE (0.12) and MAE (0.08) values suggest good predictive accuracy of the model. The high correlation coefficient of 0.65 further supports the strong relationship between the dimensions and performance. These statistically significant findings highlight the relevance of the study in providing insights into the factors that influence student performance in computer science education. The use of statistical analysis and performance metrics strengthens the validity and reliability of the findings, supporting the conclusions drawn from the study. The results of this study can serve as a basis for further research in the field, such as investigating the impact of other variables, exploring different machine-learning algorithms, or validating the findings in different educational contexts.

Future research could focus on exploring additional variables, such as socioeconomic status, prior programming experience, or learning style, in predicting student performance in computer science education. Additionally, the comparison of different machine learning algorithms, validation in diverse educational contexts, longitudinal studies, intervention studies, and replication/validation of the predictive model could further contribute to our understanding of the factors influencing student performance. Also, the researchers could evaluate the proposed theory in different educational contexts, such as traditional classroom settings, online learning, and blended learning. Additionally, the researchers could investigate the impact of the proposed theory on learners' engagement, motivation, and satisfaction with the learning process.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Ossama designed the study, collected, and processed data, analyzed data, and wrote the first draught of the manuscript. He edited and revised the manuscript to ensure quality and accuracy. Shatha reviewed the literature to support the study's findings and helped revise and edit the manuscript to ensure coherence and clarity. Both authors reviewed and approved the final manuscript, showing their commitment to the research.

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