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Analysis of Learning Characteristics of Online Learners in the Context of Smart Education

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Abstract

This article aims to explore the learning characteristics of online learners within the smart education framework, with a specific emphasis on how they might use Internet of Things (IoT) technologies to improve their educational experience. The term "online learning" refers to the process of acquiring knowledge via electronic means, most often the global web. Online education, e-learning, web-based learning, and computer-assisted learning all share this term. The challenging characteristics of such online learners for students are technical issues, lack of motivation, and slow loading times in online courses. Hence, in this research, the Internet of Things-empowered Smart Education (IoT-SE) Framework has been improved for online learners for students by leveraging IoT tech that tracks how learners interact with learning resources and their environment. This paper aims to revolutionize web-based education through tailored instructions targeting individuals' unique needs and fads as availed by the IoT-SE system. This paper offers evaluation parameters such as level of engagement among learners, retention rates on knowledge acquired while studying e-courses, and satisfaction from an online program. Besides overcoming limitations associated with conventional e-learning approaches, such systems like IoT-SE technology promise more effective pedagogy and student satisfaction for online learners.

Keywords: smart education, online learner, e-learning approaches, Internet of Things

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1. Preamble about the research verticals

1.1. Background

Online learning describes various approaches to imparting knowledge and skills via the vast and varied web. As a result, learners can finish their degree programmes without ever setting foot on campus [1]. Distance learning takes several forms, one of which is online learning, defined as acquiring knowledge and skills. Considering how recently it debuted, the Internet became widely accessible, making it a more recent kind of distant learning [2]. A course that is delivered on the Internet is known as an online class. Typically, these classes are held online using a platform for online education, in which students have access to curricular resources, track their grades, and talk to one another and the teacher [3]. To help practitioners, instructional designers, instructors, and curriculum developers understand the evolution of online learning and make educated choices when establishing high-quality online learning experiences, this research indicates using a longitudinal approach that tracks online learners over time to collect substantial evidence [4].

1.2. Motivation:

The SE method uses data analytics, interactive learning, and digital technologies to make learning more exciting and successful for students [5]. SE refers to a wide range of practices used in modern digital classrooms. It

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exemplifies how modern technology makes it easier, faster, and more convenient for students to absorb new information [6]. Smart education in online learners is the integration of technological tools into more conventional educational processes. If a teacher wants to provide his pupils with a better education, he should look at modern learning technologies like online classrooms, virtual learning environments, cloud servers, smartphones, etc [7]. The capacity of the system to counsel and anticipate the demands of learners is the most crucial feature. One kind of educational technology, SE, encourages students to apply what they study in practical situations. An intelligent learning environment aims to offer self-learning, self-motivation, and customisation services [8]. Education has many forms, but at its core, it conveys information, abilities, and values. Institutions like public schools provide the basis for formal education. Educators and universities may practise SE by maximizing the use of their financial, human, and technical assets [9,10].

Connectivity, interoperability, scalability, and processing data in real-time are the defining features of the IoT. Recognizing the significance of connection in facilitating the efficient operation of these devices is critical, given the growing number of IoT devices being implemented across different sectors [11]. More and more, the educational system and the IoT are merging. Regarding availability, engagement, and teamwork, it offers several advantages to educators and their students [12]. Educators may get precise data on students' use of specific devices and apps with the help of IoT devices in the classroom. Examining this data may better grasp a student's learning requirements, development, and passions [14]. Smart learning environments are learning solutions built into working and learning environments using the IoT-SE. Physical spaces enhanced with digital gadgets aware of their surroundings to facilitate and quicken learning are hence referred to as smart learning environments [15].

1.3. Problem definition

The challenging characteristic of such online learners for students is the technical issues, lack of motivation and slow loading times on online courses resolved by using IoT-SE;

1.4. The main objectives of the paper

- To develop a system to discuss the students learning characteristics of online learners
- Block structure has been developed based on the learning characteristics of online learners, such as technical issues, lack of motivation, and slow loading times on online courses.
- The Internet of Things enabled Smart Education (IoT-SE) has been used to design, develop, and verify the students learning characteristics of online learners.
- Using IoT-SE equivalents, the experimental results were checked for accuracy in the following areas: interaction ratio, learning rate, precision, student efficiency, and flexibility learning analysis ratio.

1.5. Organization of the paper:

Section 2 of the paper will cover similar works and the discussion. Section 3 examines the article and introduces factor models used to detect IoT-SE. The results and forum from Section 4 were compared to those of an existing methodology. Section 5 discusses the following research scope in light of the analysis presented in the preceding section, which brings the study to a close.

2. Survey and its heuristic analysis

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By describing the current state of smart education research, Singh, H et al. [16] (2020) set out to provide the Students Career Assistance System (SCAS), an initial innovative technique, with a theoretical base. The first understanding of solution design will be built upon a thorough literature review that will collect the necessary information. Based on the main results, smart education seems to be a dynamic area of study that may be enhanced using various cutting-edge technological tools. By bringing them together, we provide a novel, innovative education artefact framework as a case study; this artefact primarily consists of a mobile-based SCAS that helps students take charge of their future success in their education and careers.

Abdelrady, A. H et al. [17] (2022) detailed that higher education now routinely incorporates Information and Communication Technology (ICT) into its pedagogical methods in response to a pressing contemporary need. Several interactive platforms have been implemented to make EFL (English as a foreign language) lessons more interesting, engaging, and rewarding for students. After comparing conventional techniques of instruction that failed to include Class Point to those that did, Students of English as a foreign language reported noticeably more significant levels of e-learning satisfaction enrichment when using Class Point tool activities. Consequently, the research recommends that students of all ages and learning styles use the Class Point application to maintain their interest, motivation, and satisfaction with the learning process.

Chiu, T. K [18] (2022) discussed the necessary condition for learning is student involvement, which is fueled by motivation according to Self-Determination Theory (SDT). This study aimed to evaluate the influence of the three perceived psychological criteria in SDT on engagement in online education by administering pre- and post-questionnaires to 1,201 students in grades 8 and 9 over six weeks of online learning. The results showed that digital support strategies better addressed students' needs, that engagement levels were predicted by all needs, and that relatedness support was significant.

Han J et al. [19] (2023) explained that making use of digital resources for education is a significant factor in Technology-Enhanced Learning (TEL). This study aimed to investigate how students' views on SAOLT relate to their views on support, affect/emotion, and self-efficacy in online learning environments, with the ultimate goal of elucidating their learning strategies. Regarding online learning tools, affect/emotion and self-efficacy acted as mediators between the thorough approach, perceived peer support, and technical assistance. The results provide light on SAOLT and have educational implications for initiatives to encourage a comprehensive strategy for online learning tools, promoting high-quality education within the framework of TEL.

Jin, S. H et al. [20] (2023) introduced online learning in self-regulated learning (SRL), which is vital for students to do well academically and accomplish their goals. Conversely, students often encounter problems while using SRL in online classes. Students may be able to better self-regulate their online learning due to recent advances in using artificial intelligence (AI) to monitor and improve SRL. However, research in this area is only starting. Students rated AI applications well for helping with SRL domain-specific cognitive, behavioural, and metacognitive regulation; however, they gave them a worse grade for motivation control. Student position, student activity, and student identity are three psychological and pedagogical variables students have requested to consider while creating AI apps that might help with SRL. This study's findings can potentially educate future work on artificial intelligence (AI) technologies for online learning that are more accommodating to SRL students.

Abeysekera, I et al. [21] (2024) introduced research that evaluated the cognitive burden of learning by measuring the quality of instruction, the quality of course materials, and the quality of the Learning Management System (LMS). While assessing e-learning quality, learner happiness, and behavioral intentions to embrace online learning, it continually represented the learning memory structure. A structural equation model analysis of the data demonstrated that students' ability to control their cognitive load benefited their ability to retain information in the short term. The happiness of students and the quality of their e-learning were favourably affected by the teaching, learning material, and LMS quality. Results from first-year students demonstrated that the quality of instruction had no impact on either student happiness or the efficacy of online courses. For accounting students enrolled in online programmes, this is the first research to examine how cognitive load affects their ability to retain information.

According to Chai, J et al. [22] (2024), this study aimed to discover the key factors influencing college students' online learning experience using sentiment analysis text mining in Social Network Analysis (SNA). To isolate the core layer's most essential components, the SNA model underwent macro and micro-level parsing. The study examined the distribution of SNA model components in the mantle and peripheral shell layers and how it influences online learning experiences for college students. When designing online learning environments for college students, it is crucial to consider the many factors that impact their online learning experiences, as shown by the research.

A rising number of students in various forms of Online Language Learning with Virtual Classrooms (OLLVC) was documented by Jiang L. et al. [23] (2024). Regardless of demographic factors like age, gender, academic level, or importance, students' motivation and engagement with OLLVC were typically strong. Students' perceptions of their readiness for OLLVC influenced the relationships between their motivation, participation, and support for distant learning, which is an intriguing discovery in and of itself. These findings stress the importance of considering students' readiness to participate as a moderator of their interest in and performance in OLLVCs. The article discusses the potential consequences of allowing students to study languages online in virtual classrooms.

Eryilmaz A. et al. [24] (2024) discussed a cross-sectional study that set out to create and test a brand-new tool: the Student Online Learning Patience Scale (SOLPS). The capacity to consistently keep studying or practising in online learning settings, even when it gets tough or takes an extended period, is defined as online learning patience in this research. Research in the field and student interviews were the basis for the components that made up the scale. Research and validation factor analyses were used to examine its structure to ensure the scale's reliability and validity. To help educators develop tactics and approaches that foster online learners' patience, they have created a final SOLPS consisting of ten questions with a single dimension.

Following on from the previous section, technical issues, lack of motivation and slow loading time on online courses are taken into consideration as the significance of using a student's learning characteristic of online learners such as [16], [23] and [24]. Further, this research discusses the Internet of Things-enabled Smart Education (IoT-SE), which helps predict interaction ratio, flexibility learning analysis ratio, learning rate, precision ratio, and student efficiency ratio.

3. Internet of Things enabled Smart Education (IoT-SE) learning characteristics in online learners.

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Theoretical frameworks for online education should prioritise the learner's intrinsic motivation and active participation within a comprehensive and natural information system. Doing so while drawing attention to the exciting and thought-provoking parts of the content is ideal. Research has shown that high-quality course materials play a crucial role in distance education's success. How well a student thinks the subject is significantly presented impacts their academic success. Furthermore, students' levels of achievement in a topic are strongly related to their investment in that subject. A person's ability to absorb new information grows exponentially over time when they are enthusiastic about learning. In addition, as a result of actions including goal-setting and societal pressures, there has been an increase in the use of digital learning tools among students. The plethora of new information has considerably enhanced the educational experiences of students. The online learners' learning characteristics are discussed below.

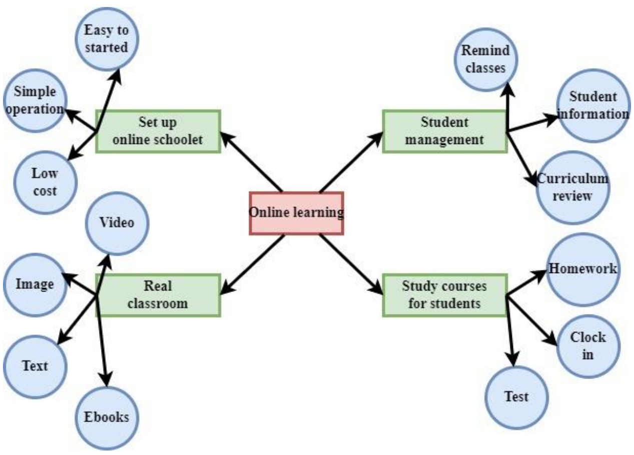

Figure 1. Online learners learning characteristics

Figure 1 illustrates the online learners' learning characteristics of its learning resource base are directly attributable to the Internet. Students have the freedom to tailor their choices to their interests and current circumstances to meet the diverse educational requirements of users at different levels. For a second, there is the potential to save both time and money by taking classes online. Online courses allow students to study whenever and wherever is most convenient. Online learning allows students to study whenever and wherever they choose, as opposed to traditional classroom instruction, which is time- and location-bound and requires many administrators. There are now more course materials than ever, and there is an explosion of learning platforms. One of the biggest challenges for online courses to enhance users' learning efficiency is sifting through a sea of learning resources to locate the ones that interest them and are a good fit for them. Another challenge is figuring out which courses to take right now. Using catalogues or search engines, which are critical instruments for collecting information, is a basic answer to the issue of information overload—using a catalogue-style classification system to arrange items in a hierarchy based on their intended use. Users may further reduce time exploring resources by searching according to the categorization.

The structural elements of online learners' learning characteristics are shown in Fig. 1. Further, the learning characteristics of online learners are discussed in Figure 2, and the student's learning is discussed as follows.

Figure 2 illustrates the learning characteristics of inline learners. Learner performance and output are two of the most critical learning product variables and presage and process factors directly affect these two. Learning grade and performance accomplished by the learner are components of online learning performance, known as E-learning performance or digital learning performance, awareness of information literacy, growth of knowledge and skills, happiness with the learning experience, etc. Higher education's trajectory in the future will be dictated by how effectively online courses are constructed and how well students do in them.

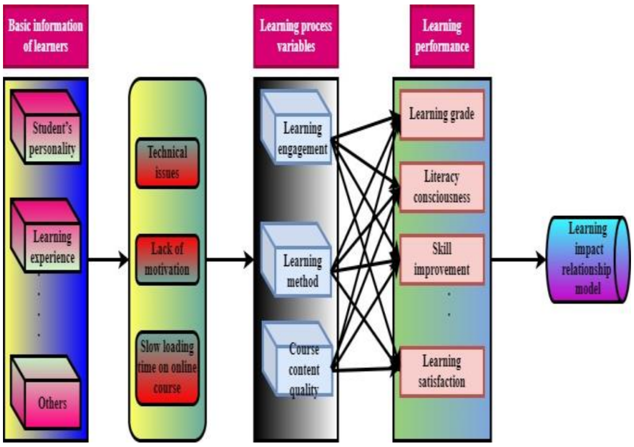

Figure 2. Students' learning characteristics of online learners

A thorough grasp of the conceptual and real-world considerations that lead to effective outcomes in online learning is vital for achieving such achievements. This research aims to determine how well online education works as a product-related variable. The expectations placed on students are that they are emotionally and cognitively capable of meeting ever-increasing benchmarks. The accessibility, adaptability, and overall quality of online general education courses compared to their conventional in-person counterparts are contributing factors. Participation in online general education classes profoundly affects students' personal growth, skill sets, viewpoints, and worldviews. The product deserves praise for accomplishing its goal of the qualities often associated with conventional schooling. Students' abilities to understand, hypothesise, analyse, reason, and debate course material are directly correlated with their level of engagement with course content. Only because it exists does it significantly affect the outcome of the educational process.

Therefore, factors that mainly influence the Flow chart SE in online learners have been discussed as follows,

Figure 3 (a) illustrates the flow chart SE in online learners. Various cultural, demographic, and psychological factors may influence online students' satisfaction levels. Research on what drives students to complete online courses—including course materials, class activities, student-to-student problem-solving, instructor initiative, communication, and guidance—was conducted to identify factors contributing to student attrition and retention. Keeping one's presence in class as a good sign of self-control was a strategy for self-regulation.

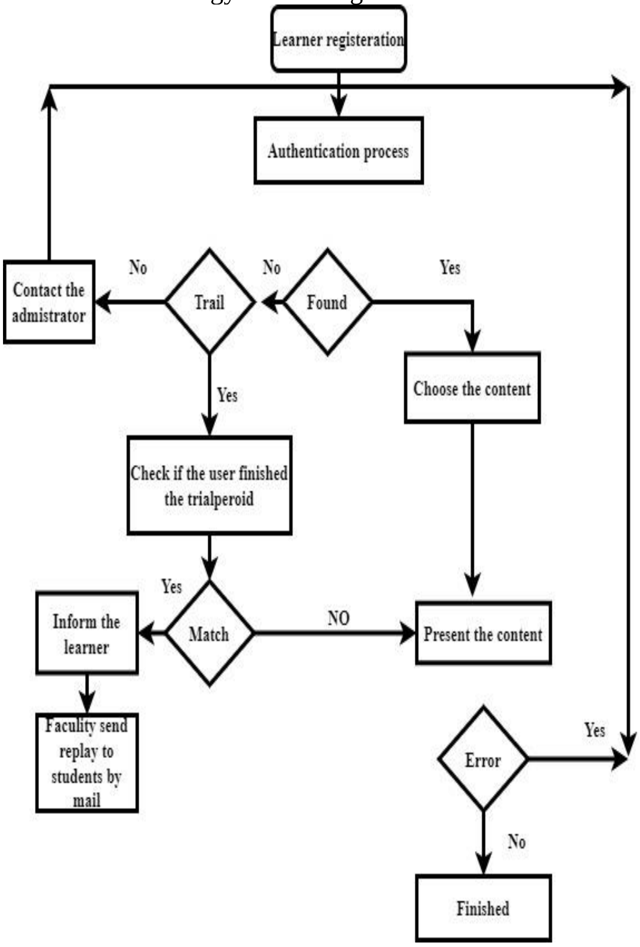

Figure 3 (a). Flow chart SE in online learners

The third component they looked at was motivation, which included the responsibilities of teachers and how they inspire their pupils, the level of effort put forth, and the surrounding environment. Some criteria, such as students' preferences, the complexity of the material, and their quality of life, were not included in the research, which is one of its weaknesses. The system should verify the user's identity using a login form; if the user is an administrator, they can upload course materials and assignments. Teachers may easily manage their students' information and tasks using these systems' user management capabilities. Because of this, administering and maintaining courses is a breeze. Everyone engaged, from students to teachers, lacked sufficient expertise in the subject matter. The move in online education away from focusing on the instructor and towards a more student-centred model has created a more authentic and engaging learning environment. The openness of educators to the idea of e-learning, the availability of technology resources, and the reliability of their internet connections were only a few of the many elements that determined the nature and rate of this transformation. An unforeseen disaster has announced the start of a crucially important moment.

From the above discussion on online learners, the learning characteristics [16], [23], and [24] need to improve in several aspects. Therefore, this advent the pathway for ***IoT-enabled SE***, which helps to predict and detect student learning characteristics of online learners as technical issues, lack of motivation and slow loading time on online courses as discussed: ***IoT-SE*** framework is discussed below:

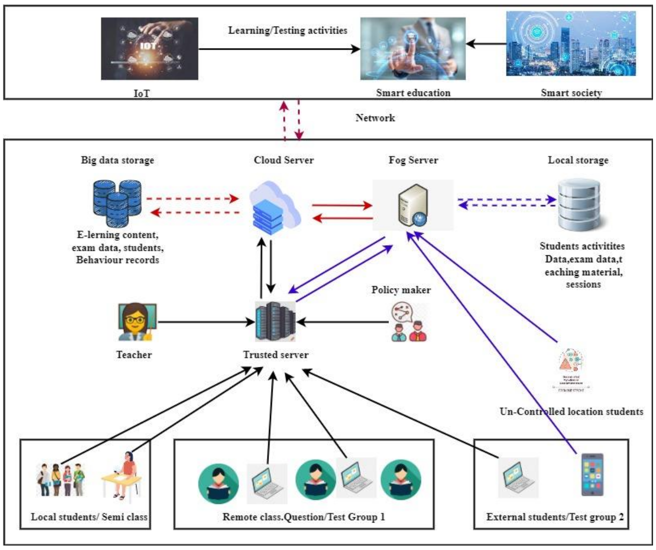

Figure 3 (b). Framework for IoT-SE

Figure 3 (b) illustrates the framework for IoT-SE for learning characteristics in online learners' aptitude tests, quizzes, and exam question sheets, which may all be administered safely with this method. Online course participants have more leeway in deciding when and how to study than those who adhere to the strict timetables required by conventional classroom instruction. The necessity to print out course materials has been eliminated, leading to decreased expenditure. Students may go through the great feature since everyone has a different learning capacity; this is one of the main benefits of this form of teaching. Online education has matured to be effectively used for distance learning and multimedia growth. This has allowed it to go beyond the traditional classroom model and better for the students. Studies examining the effectiveness of e-learning on student engagement and knowledge acquisition in studies conducted using online courses can potentially provide more trustworthy outcomes examining more traditional forms of instruction. Online courses offer more possibilities for involvement in educational pursuits than conventional teaching methods. This is the most essential reason for this. Teachers, irrespective of their level of technical expertise, may utilise these tactics to understand better and meet the requirements of their students. Transmitting data via digital games and simulations is one of the most fascinating breakthroughs. Among the most ground-breaking features of the contemporary day is the ability to do scholarly work on the cloud. Since students may access the faster fog server option via their mobile devices, it doesn't matter where they are. It doesn't alter the fact that this is true, even if there can be many advantages to taking classes online. Students don't need to be physically present in a classroom environment; they may engage remotely from anywhere worldwide if they are in the same authorised geographical region. The fog server manages its authentication needs if students' devices don't have a strong enough connection. A few students can participate in the activity while wearing smartwatches simultaneously. Students in faraway regions may be tested using this configuration since it uses reliable servers and connections with enough bandwidth.

$$\boldsymbol{O} = \sum(\boldsymbol{P}+\boldsymbol{n})^{\boldsymbol{P}} / \iint \boldsymbol{n}_{\boldsymbol{P}}\, \boldsymbol{P}\, \boldsymbol{n} \, \|\boldsymbol{P}\|\, \boldsymbol{n}\left(\frac{\boldsymbol{P}}{\boldsymbol{n}-2} * \frac{1}{2}\right) + (\boldsymbol{n}) \quad \textbf{(1)}$$

The total number of assessments for teaching quality is O, as shown in Equation 1. P denotes the attitude of the teacher, n the process of lesson preparation and scheduling, The course material is indicated by $\|P\|\, n\left(\frac{P}{n-2} * \frac{1}{2}\right)$ through the $\sum(P+n)^{P} / \iint n_P\, P\, n$ from the instruction that was successful in the assessment processes. The interaction ratio in Table 2 was obtained using equation (1) Slove.

$$\boldsymbol{S} = (\boldsymbol{T} + \prod i\, \boldsymbol{i}^2)\boldsymbol{T}^{\sum \sqrt[1]{\boldsymbol{i}} \coprod \boldsymbol{i} \exp \boldsymbol{\sigma}^2} \prod \boldsymbol{T} \quad \textbf{(2)}$$

According to Equation 2, S is the value for the essay reading evaluation. A T for learning velocity and a i for pedagogical goals. Using the flexibility learning analysis ratio shown in Figure 4, the exponential function of professional knowledge is $\exp \sigma$, and the positive guidance in harsh instruction is $(T + \prod i\, i^2)$. The problem-solving ability is then determined from equations (2) slove.

$$\boldsymbol{L} = \boldsymbol{c} - \boldsymbol{m} \times \boldsymbol{\sigma s} - (\frac{(\boldsymbol{x}_{st} - \boldsymbol{r}_{t})2}{2\boldsymbol{\sigma}_s^2} \quad \textbf{(3)}$$

The online learners are represented by L, the split classroom students by σs, and the interactive classroom students by m, with c being the assessment model of learning effectiveness in its implicit state. Equation 3, illustrated in Figure 5, represents the efficacy of interactive classroom learning; states x_{st}, r_t, L, c, and σs of the evaluation model are the space state, blocking state, split classroom, optimal running state, and observation state, respectively.

One way to describe student learning in a dynamic classroom setting is using a differential equation model.

$$\boldsymbol{x}_{\boldsymbol{n}} = \boldsymbol{m}(\boldsymbol{t}_{\boldsymbol{o}} + \Delta \boldsymbol{t}) \times \boldsymbol{L} \quad \textbf{(4)}$$

In this case, $\boldsymbol{it\, represents}$ the statistical survey's regression analysis process about the quality of instruction. $t_o$is the learning effectiveness L evaluation's statistical characteristic state function; it builds the multivariate quantitative value function in equation 4 of the regression analysis sequence; and 0is the performance measurement derived from equations 4 slove using the precision ratio in Table 3.
Using a large number of hashes increases the probability of getting 0 while looking for an item that doesn't belong to the collection. In contrast, if the number of hashes is limited, the bit arrays will have a greater number of 006s. The classroom rate is $\left(1 - \exp\left(-\frac{ml}{n}\right)\right)^l$, with a room for $f = lq \ln\left(1 - \exp\left(-\frac{ml}{n}\right)\right)$. Its primary function is to determine the optimal class size of l. If g is the lower number, then g is the most insignificant. Equation (5) represents the computation rate.

$$\boldsymbol{t} = \mathbf{exp}\left(-\frac{\boldsymbol{ml}}{\boldsymbol{n}}\right) \quad \textbf{(5)}$$

The symbols n for the number of samples, m for the mean value, and l for the error deviation n are used in statistics. Equation (5) uses the student's efficiency ratio from Figure 6 to express the value of g in the continuity equation at the precise instant.

$$\boldsymbol{f} = -\frac{\boldsymbol{n}}{\boldsymbol{m}} \mathbf{log}(\boldsymbol{t}) \mathbf{log}(\mathbf{1} - \boldsymbol{t}) \quad \textbf{(6)}$$

In this context, t stands for the error rate, n for the number of samples, and f for the mean value. Equations 7 and 8 quantify the rises and reductions of the probability ratio concerning two variables, ∂ and c.

$$\boldsymbol{\gamma}_{\boldsymbol{q}\,(\boldsymbol{m}+\mathbf{1})} = \boldsymbol{\gamma}_{\boldsymbol{q}\,(\boldsymbol{m})} + \boldsymbol{\partial}\left(\mathbf{1} - \boldsymbol{\gamma}_{\boldsymbol{q}\,(\boldsymbol{m})}\right) \quad \textbf{(7)}$$

$$\boldsymbol{\gamma}_{\boldsymbol{r}\,(\boldsymbol{m}+\mathbf{1})} = \boldsymbol{\gamma}_{\boldsymbol{r}\,(\boldsymbol{m})\,-}\ \boldsymbol{\partial}\, \boldsymbol{\gamma}_{\boldsymbol{q}\,(\boldsymbol{m})}\ \forall\, \boldsymbol{r} \quad \textbf{(8)}$$

The risk assessment matrix changes when deep learning is received for all components; equations 7 and 8 compute the $\gamma q\ m{+}1$rise probability, and the $1 - \gamma q\ m$ measure lowered the probability to the element ∂. $\forall\ r$ value equivalent to the probability of classroom performance.

$$\boldsymbol{\gamma}_{\boldsymbol{r}\,(\boldsymbol{m}+\mathbf{1})} = \frac{\boldsymbol{c}}{\boldsymbol{x}-\mathbf{1}} + (\mathbf{1} - \boldsymbol{c})\, \boldsymbol{\gamma}_{\boldsymbol{q}\,(\boldsymbol{m})}\ \forall\, \boldsymbol{r} \quad \textbf{(9)}$$

It may be seen from Equation 9 that the second variable for evaluating student performance is c. The likelihood increase dependent on student participation is defined by $\gamma_{q\,(m+1)}$. $(1-c)$indicates a lower likelihood of substituting student performance; the present session's likelihood is $\gamma_{q\,(m)}$, There are a total of $\gamma_{r\,(m+1)}$pupils, and

$\frac{c}{x-1}$represents the subject-wide probability. Discovering the optimal method concludes the learning process.

$$\max_{N\in s} \boldsymbol{C_S[PD^O]} \;\forall\; \boldsymbol{p_E \neq n_E} \tag{10}$$

Instead,

$$\min_{N\in O} \boldsymbol{E_A} \;\forall\; \boldsymbol{p_E - n_E} \tag{11}$$

Where,

$$\boldsymbol{C_S[PD^O]} \;\forall\; \boldsymbol{a_s = St_s = e_x} \tag{12}$$

And

$$\min_{N\in s} \boldsymbol{FX} \;\forall\; \boldsymbol{N(C_S) \in E_A} \tag{13}$$

In Equations (10), (11), (12), and (13), the variables $C_S[PD^O]$, p_E, n_E is used to denote the psychological data observation of the students over a time series s positive and negative emotions are identified. Based on the next student psychology and emotion data analysis, the variables E_A, a_s, St_s, and e_x are used to illustrate the student's emotional data, actions, statements, and expressions. The difference between positive and negative emotions is identified for minimizing the influence based on feature extraction, which is determined using FX. If $C_S = \{1,2,\dots,N(C_S)\}$ is the group of students, then data observations are analyzed at any instance as $E_A \times s$. Based on the statement and observations from students $N(C_S) \times E_A$, feature extraction is performed to classify emotional data. From the number of students, psychology and emotion feature extraction $N(C_S) \times E_A$ and $s \times E_A$ is processed using different data analyses and associated observation assessments.

PROTOCOL1: Session key establishes protocol
$S_{TD}: M1 = D_{K^{-}std}\ (C)_2$
If $TS'_{TS} - TS_{TS} < \Delta t$ then
If h(.) equals h'(.) then
$SK1_{S_{TD}} - TS = ID_S \otimes S_{code} \otimes RN_{TS} \otimes ID_{TS}$
Else Discard Message due to Integrity Failure
Else Discard Message due to Freshness Failure
$S_{TD} \rightarrow$
$TS: E_{SK1_{S_{TD}-TS}}\{ID_S, SK_{RQ}, TS_{S_{TD}}, RN_{S_{TD}}, MAC\left(ID_S \,\middle\|\, SK_{RQ} \,\middle\|\, TS_{S_{TD}} \,\middle\|\, RN_{S_{TD}} \,\middle\|\, SK_{RQ}\right)\}$
TS: Verifies Freshness and Message Integrity Using Hash Else Discard Msg
$TS \rightarrow S_{TD}: E_{S_{TD}-TS}\{ID_{T_S}, RN_{TS}, MAC(ID_{T_S}||RN_{TS})\}$
$S_{TD}, TS: SK_{S_{TD}-TS} = ID_S \otimes SK1_{S_{TD}} - TS \otimes TS_{S_{TD}} \otimes RN_{S_{TD}} \otimes ID_{T_S}$
$TS \rightarrow$
$S_{TD}: SK_{S_{TD}-TS}\{ID_S, SK_{REP}, TS_{S_{TD}}, MAC\left(ID_S \,\middle\|\, TS_{S_{TD}} \,\middle\|\, SK_{REP}\right)\}$
TS : Verify Freshness and Message Integrity else Message is Discarded
$S_{TD} \rightarrow TS: E_{SK1_{S_{TD}-TS}}\{ID_{T_S}, SK_{OK}, MAC(ID_{T_S}||SK_{OK})\}$
S_{TD} : Verify freshness and message integrity and activate the session critical status for its future use during encryption and decryption, else Message is discarded.

To guarantee safe communication during lectures, tests, or quizzes, students and instructors must create session keys, as shown in Protocol 1. When distributing keys, asymmetric keys are used; subsequently, session keys are employed. Based on the current keys and updated security credentials, new keys are generated for every subsequent session. At first, TS sends cypher text $(C)_2$to student S_{TD}, who uses its private key to decode it and get the security credentials S_{code}code, TS, and h(S_{code}‖ TS). Afterwards, it is confirmed that the time difference between TS and $S_{TD}$is smaller than the threshold period of Δt. If the package cannot be resealed, it will be discarded. Next, the integrity of the security parameters shared by TS is checked by comparing a hash of values. The Message is rejected if there is a discrepancy. Now, S_{TD}takes SK_{OK} of $ID_{T_S}$from S_{code}‖, $RN_{S_{TD}}$, and $S_{TD}$to determine the first-level session key $SK1_{S_{TD}} - TS$. The next step is for $S_{TD}$to share parameters with TS in order to request a session key.

Table 1. List the notations for protocol 1

Sr.no	Notation	Description
1	ID_i	Students Identity
2	ID_T	Teacher Identity
3	ID_{T_S}	Identity of trusted server
4	M	Randomly selected hash values at TS
5	S_{Code}	Secret code generated by TS
6	$H(ID_S)$	Hash identity ID_S
7	$(C)_2$	Cipher text of students TS
8	RN_{TS}	The random nonce value generated by TS
9	TS_i	Timestamp of student device
10	$h(.)$	Hash function
11	SK_{REP}	Session key replay
12	SK_{OK}	Confirmation of session key

Regarding problem detection, IoT-SE activation functions are like a collection of transfer functions applied to students' learning. Input and feedback are considered to determine the required output efficiently for students' learning characteristics in online learners.

4. Experimental analysis

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The following are some of the ways in which the study found that the IoT-SE outperformed interaction in predicting and validating online learners' learning characteristics: interaction ratio, learning rate, precision ratio, efficiency of the student, and flexibility of the learning analysis.

Dataset Description: 100 students were taken from [25] for this experimental analysis. Learn more about online learning, what makes a student successful, what to look for in an online learning programme, and what they can do to be ready for online education in this helpful resource for students.

Table 2. Interaction ratio for students

No.of.students	SCAS	OLLVC	SOLPS	IoT-SE
10	30.2	39.3	25.3	65.9
20	35.1	48.2	62.7	76.1
30	10.5	23.8	42.3	63.8
40	28.3	22.9	38.2	59.9
50	31.2	20.3	40.4	62.7
60	25.2	36.5	49.8	69.2
70	17.9	26.7	40.5	62.3
80	72.3	48.3	53.6	63.2
90	45.3	36.3	52.6	67.8
100	40.3	53.3	38.3	82.7

Table 2 illustrates the interaction ratio for students' intelligent education system powered by big data, which has progressed to this point. Looking at students' knowledge capacity and the data that instructors acquired allowed us to interact with their learning patterns in this research. The algorithm's accuracy drops with decreasing sample size, even as the rate increases. When tested on the study's balanced data set, the interaction ratio of all classifiers is about doubled. Everything has improved and is at a pretty high level after the data set experiment concluded. The results show that resampling makes the dataset fairer, which helps the classifier uncover students at risk and increases the number of incorrect predictions for those students. Even the most cautious students make mistakes from time to time. Compared to other existing methods, SCAS, OLLVC, and SOLPS, the proposed IoT-SE is an interaction ratio for students and can be calculated using Equation (1). The suggested approach outperforms the current strategy by an interaction ratio of 82.7%.

Students' current risk level may be determined, appraised, and their capacity to learn from the course can be predicted by carefully observing the flexibility learning analysis ratio, as shown in Figure 4.

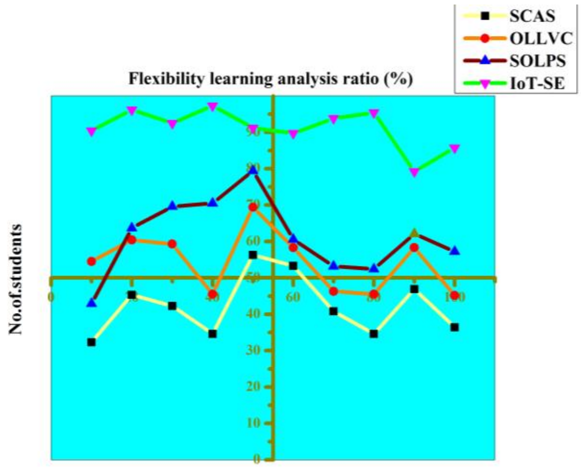

Figure 4. Flexibility learning analysis ratio

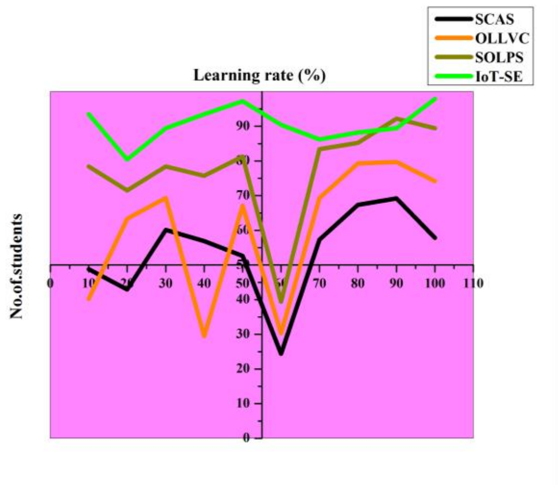

Figure 5. Students learning rate in learning characteristics in online learners

The suggested IoT-SE is an adaptable student-learning analysis ratio that can be computed using Equation (2), and it outperforms the current techniques SCAS, OLLVC, and SOLPS. That is why the model's efficacy is severely diminished if it can't accurately identify at-risk students. By combining the accuracy and recall rates of each model, we get the following graphs. There was a considerable increase in accuracy and recall compared to the machine learning findings for the balanced sample. When comparing the original unbalanced model to the balanced data sample, the findings show that the latter is more effective and flexible. Compared to the alternative strategy, the suggested approach saw an 85.72 per cent increase in the IoT-SE flexibility learning analysis ratio.

Figure 5 illustrates the students' learning rate and characteristics in online learners in the autonomous learning environments made possible by SE powered by students. Students have more flexibility in their study schedules using the IoT-based education system. In contrast, digital learning cannot enhance teachers' comprehension of their pupils. The changes in the profession have made it impossible to train teachers in the same manner as before. If they wish to assist their pupils in learning more effectively, teachers want to know what those children require. Compared to other existing methods, SCAS, OLLVC, and SOLPS, the proposed IoT-SE is students' learning rate in learning characteristics in online learners and can be calculated using Equation (3). The proposed method IoT-SE student's learning rate in learning characteristics in online learners increased by 97.9% compared to the other method.

Table 3. Learners precision ratio for IoT-SE

No.of.students	SCAS	OLLVC	SOLPS	IoT-SE
10	40.2	57.7	35.2	75.3
20	38.9	25.3	23.9	70.3
30	65.3	45.3	49.6	74.2
40	42.2	32.7	29.5	77.3
50	52.2	55.4	40.5	86.6
60	59.2	53.2	43.3	82.5
70	32.3	48.6	18.2	81.3
80	46.3	59.6	38.2	50.7
90	53.3	39.3	26.2	44.2
100	52.2	55.4	41.9	85.6

Table 3 illustrates the learner's precision ratio for IoT-SE by gathering student learning data. It assessed their current state of education—teachers' students' learning strengths and areas for improvement by routinely evaluating their progress and offering tailored feedback. Teachers will be able to identify issues with their schools earlier. According to this school of thinking, depriving an organisation of its authority is morally commendable. However, when student errors are considered, the opposite is confirmed. Permitting these errors to persist increases the likelihood of suffering losses. Studying English is becoming more challenging due to term constraints. However, even after a massive loss of resources, the killed representative may still get back to the student level according to the organization's restricted gaining design. This gives the student the freedom to pursue their interests in whichever way they see fit. Compared to existing methods, SCAS, OLLVC, and SOLPS, the proposed IoT-SE is the learner's precision ratio and can be calculated using Equation (4). The proposed method, the IoT-SE learner's precision ratio, increased by 85.6% compared to the other method.

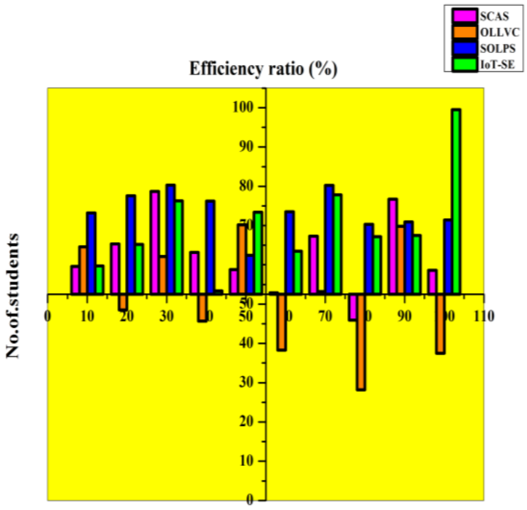

Figure 6. Student efficiency ratio

The student's efficiency ratio is shown in Figure 6. Personalized learning and critical thought are the two pillars upon which information scaffolding rests. Students are given more choices in their study habits using mobile pedagogy, which is a blend of reactive and synchronous learning strategies. How pupils study has been significantly influenced by technological advancements. Because there is a sense of belonging in a virtual learning community, students are more likely to participate in self-paced, independent study in mobile learning environments. The achievement of the learning goal relies on the student's performance in a broader context. This is why a more analytical mindset is required for success in an online classroom. The findings support the idea that developing one's capacity for higher-level thinking in digital contexts is crucial for advancing one's cognitive development. This evidence suggests that our ability to analyze, evaluate, and create digital educational materials has improved. When studying how digital education affects students' study flexibility in digital settings, creative pedagogies take into account a variety of educational circumstances and abilities, including reasoning and personality. Regardless of context, educators and students alike reached the same conclusion: students' use of mobile devices enhanced classroom education. The student's efficiency ratio, or IoT-SE, may be determined using Equation (5) and is compared to other current approaches, such as SCAS, OLLVC, and SOLPS. Compared to the alternative strategy, the efficiency ratio of IoT-SE students was enhanced by 98.5% using the suggested approach.

Tables 3 summarize the above comparisons.

Table 3 Comparison Summary for online learners

Metrics	ELM	DDFD	CBM	SVM-ANN
Interaction ratio(%)	40.3	53.3	38.3	82.7
Flexibility learning analysis ratio(%)	36.4	45.2	57.2	85.72
Learning rate (%)	57.8	74.2	89.4	97.9
Precision ratio (%)	52.2	55.4	41.9	85.6
Students efficiency ratio (%)	58.6	37.5	71.4	99.5

The proposed IoT-SE improves the interaction ratio, flexibility learning analysis ratio, learning rate, precision ratio and student efficiency ratio by 82.7%, 85.72%, 97.9% and 85.6%, 99.5%, respectively.
Therefore, future work discusses fault diagnosis power equipment in industries with IoT-SE assistance to validate the interaction ratio, flexibility learning analysis ratio, learning rate, precision ratio and student efficiency ratio results.

5. Summary about the research verticals

Using IoT-SE approaches, SCAS, OLLVS, and SOLPS are successful; the benefits are accurately anticipated, and the experimental analysis is persuasive. These methods are comparable to students' learning characteristics but cannot be predicted. Construct an IoT-SE as part of this study to meet the growing need for online learners' traits related to learning. Research into online learning assessment must be expanded to improve education. In light of smart learning systems made possible by big data, education specialists should reevaluate long-held beliefs about the nature of learning, while learning environment architects should concentrate on creating novel classroom layouts. Improving the data-gathering method in follow-up research is vital because it impacts data collection significantly. This is because relevant departments and students must participate and interact. To help get the most out of that research, this paper aimed to lay forth a paradigm for feature-dependent data inquiry. Researchers interested in the mental effects of online learning, isolation, and related behaviors could find this helpful approach. The foundation of the time-dependent approach is the students' feelings, words, and deeds. Students' ability to put their newfound knowledge into practice emphasizes the change from positive to negative expressions. Thanks to this transition detection, stable safety measures are better evaluated. Once the data has been classified, the feature extraction probability is calculated by considering the whole student body and several mood metrics.

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