A Machine Learning Approach for Detecting Individual Learning Style using Eye Tracking and Accelerometer

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ABSTRACT
The rapid growth and widespread adoption of e-learning platforms have transformed access to education, yet most systems still rely on one-size-fits-all instructional strategies that fail to account for individual cognitive differences. In addressing this limitation, adaptive e-learning environments increasingly depend on learner models—particularly learning styles—to personalize content delivery and instructional pathways. However, existing methods for identifying learning styles, such as self-report questionnaires and log-based LMS analytics, suffer from subjectivity, sparsity, and limited sensitivity to real-time cognitive engagement. This study develops a machine learning approach that integrates biometric sensors and behavioural data to infer learner preferences more robustly and objectively. Using a custom e-learning platform, we collected synchronized eye-tracking and mouse interaction data alongside assessment performance from undergraduate students engaging with a networking course material. An NBTree-based classification model fused these multi-source features to identify learning styles aligned with the Felder–Silverman framework. The system achieved an accuracy of 88.06% and an R^2 value of 0.7307, outperforming traditional questionnaire-based methods. The platform's effectiveness was further evaluated using the four levels of the Kirkpatrick Model, demonstrating high learner satisfaction, substantial learning gains, positive behavioural transfer, and strong perceived relevance. This study contributes a validated baseline for multi-source, ML-driven learner modeling and provides an approach for dynamic, non-intrusive, near real-time personalization in adaptive e-learning systems.

General Terms
Machine Learning, Adaptive Learning Systems, Educational Technology, Learning Style.

Keywords
Learning style, Eye Tracking, Accelerometer, E-Learning, Felder–Silverman Model

1. INTRODUCTION
E-Learning has experienced rapid global growth, transforming significantly from its early stages of computer-assisted instruction to the current fourth generation, characterized by massive open online courses (MOOCs) and ubiquitous learning systems [1], [2]. This growth has been fueled by the expansion of the internet, an increase in individuals with regular Internet connection, combined with the falling cost of high-resolution digital devices that can access online and technology-enabled platforms displaying high-resolution media [3]. Over the past decade, this has made online education increasingly accessible and adaptable for a global audience and has driven a massive transition toward these E-Learning systems [4]. E-Learning represents a unique opportunity for students to learn independently, regardless of time and place, connecting them with a virtually limitless wealth of information.

In higher education, E-learning is now an integral part of the ecosystem, serving as a primary instrument for universities to reach broader user bases without the constraints of time or geography [3]. This adoption of E-Learning is particularly visible in the proliferation of Massive Open Online Courses (MOOCs) [5], and the expansion of corporate and industrial training to include online training modules for enhancing industry knowledge and skill sets [4]. E-learning also offers a multi-representational environment where digital materials can be shared in various formats, including video, audio, and interactive simulations [6]. Emerging technologies like virtual reality (VR) [7] and simulations have extended the reach of e-learning into specialized fields such as medical and engineering training [8]. The benefits of this adoption are manifold: e-learning is cost-effective regarding physical infrastructure, compensates for academic staff scarcities, and offers flexibility that allows students, including adult learners, to maintain professional careers while pursuing educational goals [9]. These systems allow for both asynchronous learning, where students progress at their own pace, and synchronous interaction with instructors through live conferencing and real-time chat [6]. By providing access to a diverse population and modernizing instructional delivery, e-learning has become a tool for both personal development and organizational excellence [10].

Despite the widespread adoption, one primary challenge facing modern e-learning is the prevalence of courses that suffer from a "one-size-fits-all" approach, where every learner receives an identical experience and static content [11]. This traditional paradigm treats learners as a homogeneous entity, delivering uniform content and instructional sequences regardless of the individual student's specific cognitive requirements, prior knowledge, or unique strengths [12],[13]. Many educational institutions struggle to move beyond these traditional pedagogical paradigms, as they simply digitize static lecture notes or textbooks rather than leveraging the technology's full interactive potential [4].

This mismatch between instructional delivery and learner diversity leads to sub-optimal learning outcomes, increased dissatisfaction [14] and high dropout rates, as students experience cognitive overload or boredom with content that is not personalized to their needs [2]. Consequently, there is a need for responsive and "intelligent" E-Learning systems that can adapt learning content and delivery to the diverse ways humans assimilate knowledge either visually, auditorily, or through active experimentation [15],[16].

To address these challenges, researchers have shifted toward adaptive learning systems that leverage learner models to tailor the pedagogy and personalize curriculum content [14]. A learner model serves as a representation of a student's cognitive and non-cognitive characteristics [17]. By building a learner model from both static and dynamic data, such systems can dynamically adjust content presentation, navigation paths, and pedagogical strategies to meet individual requirements [18].

Learning styles remain a significant parameter within these models, serving as relatively stable indicators of how a learner perceives, interacts with, and responds to information [19]. While some scholars debate the stability of these styles, there is a consensus that instruction is most effective when it aligns with a learner's cognitive preferences [11]. Proponents argue that diagnosing individual styles, such as the visual or verbal dimensions of the Felder-Silverman Learning Style Model (FSLSM), provides a necessary foundation for improving motivation, retention, and overall learning performance [4]. When instructional materials align with a learner's preferred style, students often exhibit higher levels of motivation, confidence, and overall academic performance. Personalization based on these styles has been empirically shown to improve academic success and overall student satisfaction [20].

Effectively identifying these styles remains a challenge for educational researchers. Traditional identification methods rely on self-reported questionnaires, such as the Index of Learning Styles (ILS) based on the Felder-Silverman model or the Visual, Auditory, Read/Write, Kinesthetic (VARK) questionnaire [21]. These tools are popular because they are simple to implement, easy to interpret, and grounded in established educational psychology [22]. However, they are inherently static, subjective and assess a student's preferences only at a single point in time. Also, the length of these questionnaires (containing over 44 items and sometimes more than 100) frequently leads to "questionnaire fatigue" [23], causing learners to choose answers arbitrarily [21].

A more unobtrusive and scalable approach involves applying machine learning (ML) models and data mining to digital traces from Learning Management Systems (LMS), such as clickstreams, time spent on specific materials, navigation patterns, and forum interactions [24]. While this method does allow for continuous monitoring and the detection of changes over time, it often results in shallow Behavioural inference [23]. Log data alone provides only a partial, unidimensional picture of the complex learning process [24]. It is difficult for such methods to distinguish whether a long "dwell time" on a page indicates a reflective learning style or simply a distracted student [12], leading to potential inaccuracies.

Recent advances in technology have introduced biometric data sources, such as eye-tracking or mouse movement patterns for learning style detection [25],[23]. Eye-tracking records point-of-gaze (POG) and temporal information about where attention is focused which is highly correlated with cognitive processing preferences [26], while mouse movement can reflect a user's engagement with learning content [27]. While these biometric sources provide objective, non-biased biodata that avoids the pitfalls of self-suggestion, they often have limited robustness and can be skewed by environmental factors like lighting and other technical restrictions [23].

A significant research gap exists in the development of robust machine learning models that combine LMS log data with biometric sensors to detect learning styles [24]. Most current attempts are limited to single-sensor data and lack the validation provided by secondary biometric streams, such as combining gaze data with accelerometer-based motion data [28]. This study is motivated by the need to create a more precise and responsive e-learning environment that moves beyond the limitations of questionnaires [13]. By utilizing an ensemble NBTree model and evaluating the system's impact through Kirkpatrick's Model [29], this research aims to provide a comprehensive baseline for technical accuracy and pedagogical effectiveness in intelligent E-Learning systems.

2. RELATED WORKS

[3] explored the relationship between personality traits and learning preferences among millennial students using a quantitative, cross-sectional design. Their methodology utilized the Myers-Briggs Type Indicator (MBTI) and the Felder-Silverman Index of Learning Styles (ILS) to assess 190 postgraduate students. The researchers achieved a notable finding: all MBTI dichotomies (Extroversion vs. Introversion) were positively correlated with their corresponding FSLSM dimensions (Active vs. Reflective), suggesting that personality can predict learning styles. However, this approach is fundamentally limited by its reliance on self-reported data, which is often criticized for being subjective, static, and prone to questionnaire fatigue.

[30] developed a machine learning approach to detect learning styles by mining digital traces within a Moodle LMS environment. Their methodology involved extracting 16 combinations of features from learner logs—such as the number of exercises visited and time spent on specific content types—to train various classifiers like Support Vector Machines (SVM) and Random Forest. While they achieved a high consistency rate of 80% to 92% compared to manual marking, their model is limited by its reliance on digital traces, which provide a unidimensional picture of the learner. Log-based data is inherently probabilistic; for instance, a page being open does not guarantee the learner is cognitively engaged.

[5] applied a variety of data mining algorithms to user interaction logs to determine FSLSM dimensions. By using the WEKA tool to mine activity files, they found that a modified Decision Tree (J48) classifier performed better than other algorithms in identifying specific learning preferences. Despite these achievements, log-based identification remains limited by its shallow Behavioural inference.

[31] proposed a model for extracting Behavioural patterns from a generic Learning Management System (LMS) to detect learning styles. Their methodology analyzed digital traces such as scrolling Behaviour and time spent on pages to build user models within systems like Moodle. While their results demonstrated the potential for automatic identification, a major limitation was that the engineered features mapped to only one dimension of the FSLSM.

[32] investigated the efficacy of using mouse movement and facial expressions to detect online learning engagement. Their methodology involved capturing scrolling speed and cursor location every 250 milliseconds, using this data as a proxy for reading speed and cognitive effort. They achieved a high recognition rate of 94.60% when mouse Behaviour was used as a reference for image labeling. Despite this success, the study highlighted that single-sourced motion data is limited because it cannot precisely determine where a user's visual attention is focused. Furthermore, motion-based metrics can be skewed by the length of the content page; if a page is too short to require scrolling, the lack of recorded data significantly degrades the model's predictive power.

[33] conducted research confirming a correlation between mouse movement patterns and the global/sequential dimension of the FSLSM. Their method involved capturing mouse coordinates, speed, and acceleration as a user interacted with displayed learning objects, analyzing the data via MATLAB.

The study achieved a strong correlation as proposed, indicating that manual interaction reflects a learner's information-processing style. However, single-sourced motion data provides only a limited picture of learning activity. It cannot determine exactly where a user's visual attention is focused, making it difficult to distinguish between active reading and a daze, thereby necessitating the integration of more robust biometric sensors like eye-trackers.

[34] utilized Tobii Pro Glasses 2 to record gaze Behaviour in Turkish medical students during cognitive tasks. Their methodology focused on extracting metrics such as fixation duration and saccadic movements to correlate with FSLSM dimensions and academic GPA. They achieved significant results linking visual learning preferences to longer fixation durations and higher GPAs among female participants. However, the study was limited by a small sample size (n=20) and modest effect sizes, and it failed to cross-validate these findings with data from other sensors.

[35] explored the use of a low-cost eye tracker to distinguish between visual and verbal learners among 90 engineering students. Their approach utilized a time-based assessment by subdividing interaction duration into ten intervals, measuring the percentage of fixation duration on graphical vs. textual content. They found a significant relation between gaze data and learning styles, but only when content followed a specific split-screen arrangement. This highlights a major limitation of single-sourced eye tracking in that its accuracy is highly dependent on document layout, and the system struggled to recognize more complex dimensions like active/reflective or sequential/global styles.

[36] addressed the visualizer/verbalizer axis by analyzing gaze paths on "pictures-in-text" arrangements with a Tobii eye-tracker. Their methodology triggered natural reading habits through easy tasks and compared gaze predictions to self-reported ILS scores. They achieved general accuracies ranging from 53% to 77%, demonstrating that eye movements are reliable indicators of sensory preferences. Nevertheless, they concluded that single-sourced eye tracking is insufficiently robust for the diverse content found in real-world e-learning. Single-sourced data lack the cross-validation provided by secondary biometric streams, such as accelerometers, which are necessary to distinguish between active information processing and a passive gaze.

[26] proposed a straightforward approach to record the time participants gazed at specific learning objects using an ordinary webcam. Their study generated heatmaps to infer learning styles, demonstrating significant differences in the time verbal and visual learners spent on their preferred content types. While this method is direct and non-intrusive, it is considered too simplistic for large-scale LMS applications where more robust metrics and multi-sourced data are necessary to minimize errors and ensure the reliability of the learner profile.

[37] investigated the relationship between cognitive style and eye-tracking patterns by measuring fixations and gaze ratios. Their methodology involved presenting participants with balanced visual and textual objects while an eye-tracker recorded their interactions. The results validated the Verbalizer/Imager axis, showing that imagers concentrate on visual content while verbalizers focus on text. However, this single-sourced approach is insufficient because eye fixations alone cannot reveal all internal cognitive processes.

3. METHODOLOGY

This study adopts an experimental research design complemented by survey-supported data collection to detect learning styles. An experimental E-Learning platform was set up to monitor users, log user activities and capture biometric data from two sources as the users interact with learning objects. The E-Learning platform takes a multi-layered approach to ensure that real-time Behavioural data from eye-tracking and the mouse sensors are collected for analysis and cross-validation.

3.1 Initial User Model

The E-Learning platform architecture as shown in Figure 1 below follows a modular structure where users initially complete a self-reported Index of Learning Styles (ILS) questionnaire and a pre-course assessment to establish an initial user model. On completion of both assessments, the user then enrolls in a course, interacts with the course and completes an assessment at the end of each subsection of the course.

3.2 Learning Object Repository

Subsequent components include a Learning Object repository and User Activities mapped to the four dimensions of the Felder-Silverman Learning Style Model (FSLSM) as shown in Table 1, which users interact with while their biometric signals are recorded.

Table 1. Mapping of Learner Objects to FSLSM dimensions

Dimensions	Learner Characteristics	
Processing	Active	Reflective
	Exercise Code Execution Animation	Hypertext access Lecture delivery
Perception	Sensing	Intuitive
	Concrete Content (Hypertext) Examples of Concept Exercises Text Revision	Abstract Content (Hypertext)
Input	Visual	Verbal
	Narrative Text Open Textbook Diagram/Chart/ Animation Code Execution	Hypertext PowerPoint slide show Lecture Delivery
Understanding	Sequential	Global
	PowerPoint slide show Lecture Delivery	Visiting course outline

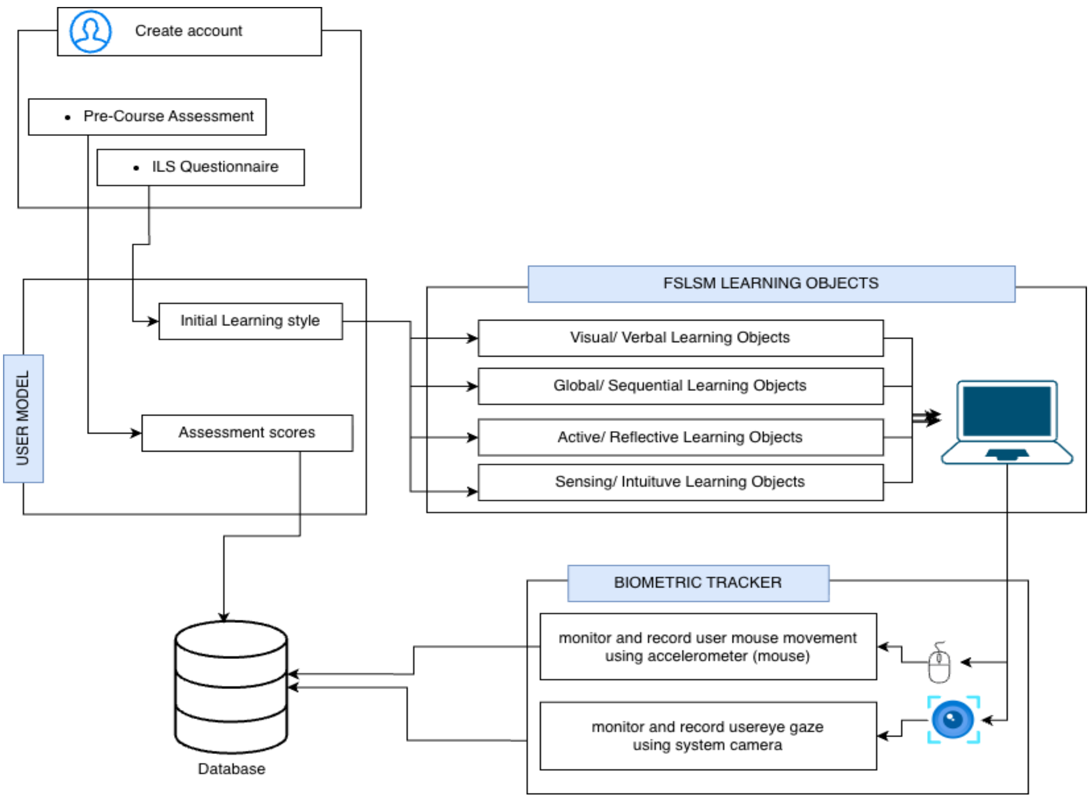

Figure 1. The E-Learning Platform Architecture

3.3 Biometric Tracking and Data Processing

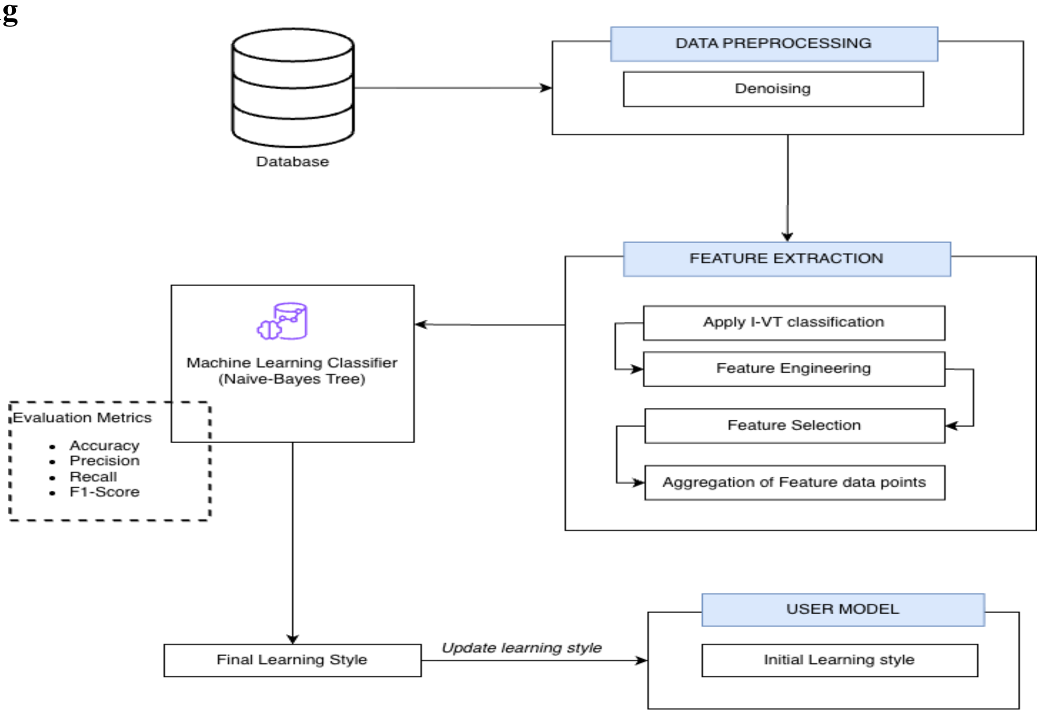

Figure 2. Overview of the data processing and ML model

The design of the biometric tracking component for capturing and analyzing the biometric data as shown in Figure 2, is organized into four main modules: pre-processing, extraction, classification, and decision.

a. Data Preprocessing

The captured biometric data (eye gaze, a, and mouse movements, g) undergoes several preprocessing steps to ensure signal integrity. A non-weighted moving-average filter by [38] is applied to the gaze data to remove random fluctuations and camera-induced noise. Gaze data points are then sampled at 28-35 frames per second to normalize the information volume and mitigate sensor variability as in equation 1.

$$a_o[n] = \frac{1}{2*N+1}\sum_{k=-N}^{N} a[n-k] \qquad (1)$$

where a_o is the output, n is the current sample, N represents the window size, k represents each sample in the window size.

b. Feature Extraction

Velocity Threshold Identification (I-VT) classification method of [38] is used to assign a velocity v to each data point by calculating the change in coordinates over time as shown in equation 2

$$v_n = \frac{|x_n - x_{n-1}|}{|t_n - t_{n-1}|} \quad (2)$$

where t is the timestamp of the data points.

Points are then categorized based on a specific threshold: velocities v_n lower than the threshold v_t are classified as fixations F (moments of stillness), while those above are marked as saccades S (rapid movements):

$$f(v_n, v_t) = \{F_n,\ v_n < v_t\ S_n,\ v_n \geq v_t\} \quad (3)$$

Eye-tracking features are extracted by analyzing the duration and spatial distribution of gaze points. The primary features included fixations, representing periods where attention is focused on a specific object, and saccades, representing the rapid transitions between points of focus. Spatial metrics such as intensity, I, (the aggregation of consecutive fixations on specific learning objects), heat maps, H, (the aggregation of all fixations on an object) and gaze plots, P, (the chronological path of gaze) are generated to represent visual attention patterns as represented in equations 4, 5 and 6 respectively.

$$I = \sum(t_n \mid v_n \in F_n) \quad (4)$$

$$H = I * n \quad (5)$$

$$P_n = (F_n \mid t_n = t_{(n-1)} + r) \quad (6)$$

where r is the rate at which the data points are sampled.

Furthermore, gaze transition entropy T_e between learning objects LO is calculated to quantify the unpredictability of the user's scan paths as in equation 7.

$$T_e = (LO_{i+1}[P_n] - LO_i[P_n]) \quad (7)$$

Accelerometer features focused on quantifying the user's manual interaction with the learning interface. Metrics included vertical scroll speed, VS, which estimates reading speed based on the rate of page navigation, and attention duration, which used mouse pointer movement to estimate the user's attention span as shown in equation 8.

$$VS = (g_n - g_1, a_n - a_1) \quad (8)$$

These features are associated with the learning object category (image vs. text) and the user's assessment scores to create a robust, multi-channel dataset.

$$LO_i = (F_n, I, H, P, VS) \quad (9)$$

c. Classification and Decision Machine Learning Models

The study adopted a hybrid machine learning model known as the Naïve-Bayes Tree (NBTree). This hybrid approach combines the segmentation benefits of decision trees with the evidence accumulation capabilities of Naïve-Bayes classifiers. NBTree typically outperforms both individual models, particularly on large or complex datasets, while maintaining the interpretability. The model recursively splits data based on feature values to create nodes, with Naïve-Bayes classifiers at the leaf nodes to determine if instances belong to a specific learning style class.

The model generates a set of possible labels, l_n, for the dataset where each label is a Felder-Silverman Learning Style Model (FSLSM) dimensions denoting the learner's learning preferences:

$$NB: \{LO_i, T_e\} \rightarrow \{l_1, l_2, \ldots, l_n\} \quad (10)$$

The preferred learning style for each FSLSM dimension is the label with the highest count.

4. EXPERIMENT AND RESULTS

The participants for the testing phase were undergraduate students recruited from a Computer Science Department, Federal University of Technology, Akure. A non-probabilistic sampling method was utilized for reasons of practical accessibility and reduced cost. The final dataset used for training the model comprised 100 instances of students engaging with digital content. This specific population was selected based on their existing familiarity with e-learning systems, which provided valuable feedback and helped reduce errors during the interaction monitoring process. Participants were given clear instructions to minimize unnecessary head movements or screen switching to ensure the integrity of the sensor data. The demographic breakdown of the participants is shown in Figure 3.

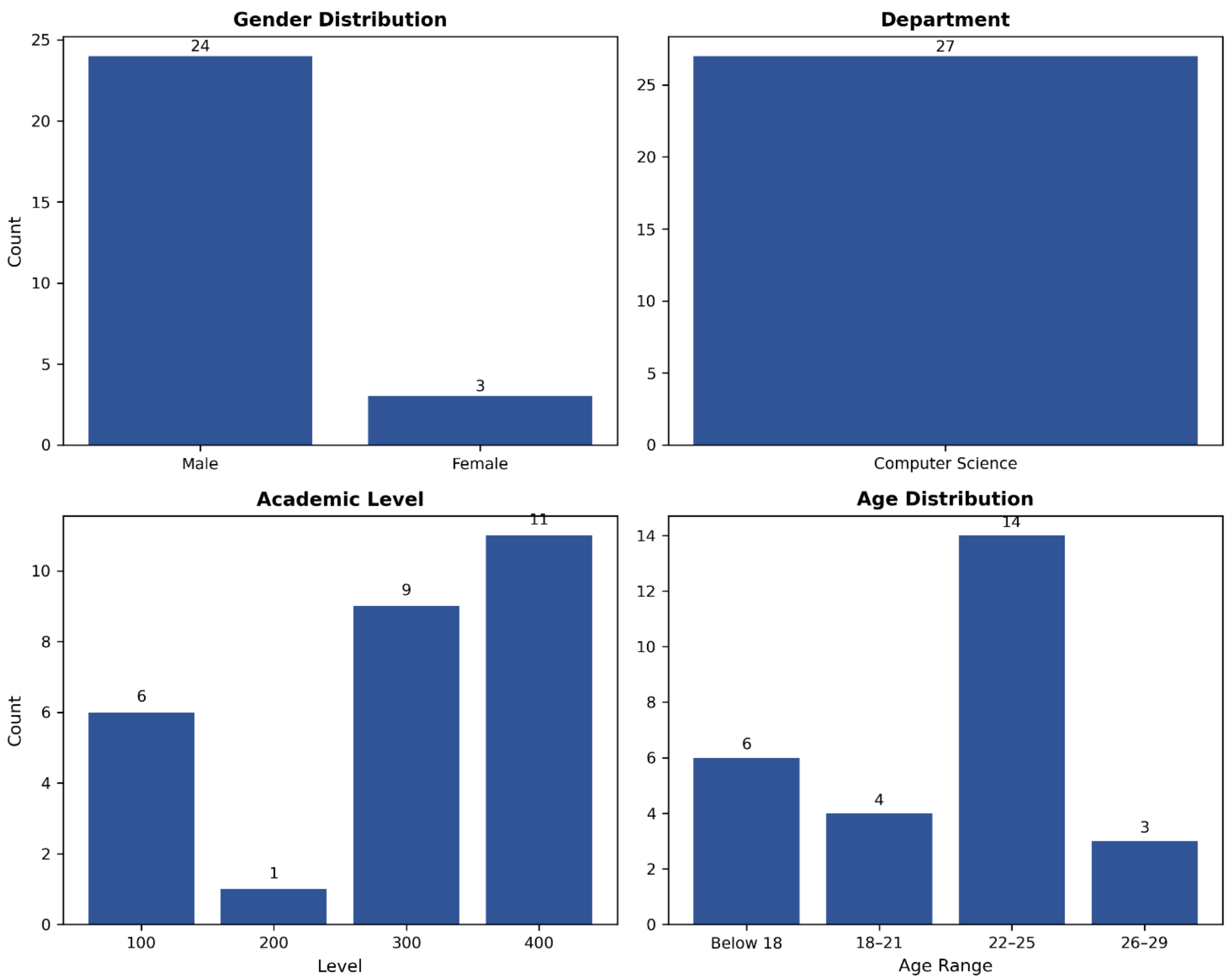

Figure 3. Demography of the learners

The experimental E-Learning platform was developed using the Flask framework and Bootstrap for a structured, responsive user interface. The learning task was a foundational course titled "Introduction to Networking", which was systematically divided into modules and lessons. Each subtopic contained diverse Learning Objects representing FSLSM dimensions, such as infographics for visual learners and text descriptions for verbal learners as depicted in Table 2. During the study, participants read through the material at their own pace and completed a sequence of activities, including quizzes and post-tests, to evaluate knowledge acquisition.

Table 2. Samples of the FSLSM Learning Objects used

Learning Object	Content
Text	Networking is the practice of connecting computers and other devices to share resources and information. In essence, it enables communication between these devices, allowing them to exchange data and collaborate. Networks can vary in size and scope, from small local networks within a single building (Local Area Network or LAN) to expansive global connections (Wide Area Network or WAN). The foundation of networking lies in protocols, which dictate the rules and conventions for data transmission. The most ubiquitous protocol suite is TCP/IP, defining how data is packaged, addressed, transmitted, and received across networks.
Image	define network.jpeg
Example	Consider a scenario where multiple computers in an office are connected to a local network. Employees can share files seamlessly, printers can be accessed by anyone on the network, and collaborative tasks can be achieved more efficiently. Additionally, these computers may have access to the internet through the same network, enabling communication beyond the local environment. In this way, networking facilitates resource sharing, communication, and collaborative work.
Revision	What is the fundamental purpose of computer networking?
Revision	How does the size and scope of a network impact its functionality?
Text	The history of computer networking traces back to the mid-20th century, with significant developments leading to the interconnected world we know today. One pivotal moment in networking history is the creation of the ARPANET (Advanced Research Projects

	Agency Network) in the late 1960s by the U.S. Department of Defense. ARPANET, designed to facilitate communication among researchers, is often considered the precursor to the modern internet. It utilized packet switching technology, a key innovation allowing data to be broken into packets and sent independently across the network before being reassembled at the destination. This breakthrough not only improved reliability but also laid the foundation for the scalable and decentralized nature of today's internet.
Image	network history.jpeg

User interactions were monitored using two primary sensors: a webcam-based eye tracker and a mouse. The eye tracking was implemented via a custom Python script utilizing the MediaPipe library to track facial landmarks and pupil positions in real-time through the webcam. Simultaneously, the mouse recorded tri-axial data points to capture vertical scroll speed and page navigation. To ensure proper synchronization, the system recorded both data streams concurrently, using timestamped identifiers to tie eye gaze and mouse movement to specific learning objects and user IDs. The Heatmap showing intensity of user gaze on learning objects in two sides of FSLSM is depicted in Figure 4. This setup allowed for a seamless, non-intrusive capture of the user's LMS and cognitive activities.

The training dataset was aggregated into a single, comprehensive structure from user features, extracted features from eye gaze data, mouse interaction patterns, learning object characteristics based on the FSLSM model, assessment scores, and initial Index of Learning Styles (ILS) values. The prepared dataset was then used to train a Naive Bayes Tree (NBTree) model. During training, the model performance was optimized through hyperparameter tuning of specific parameters, such as the maximum depth of the tree.

Gaze metrics, particularly fixation duration and saccades, served as primary indicators of where information was being processed and how attention shifted. The analysis revealed that gaze intensity and gaze transition entropy were highly informative for identifying diverse exploration patterns. Specifically, the gaze intensity/dispersion acted as the root node in the NBTree model, showing the highest utility for user learning style segmentation. From the mouse data, vertical scroll speed was a key feature for estimating reading rates, while mouse-based attention duration quantified manual engagement levels. By fusing these biometric metrics with assessment scores, the model achieved an accuracy of 88.06% and an R^2 value of 0.7307 as shown in Table 3, significantly outperforming traditional questionnaire-based assessments.

Table 3. Model Evaluation Metrics

NBTree Model Metrics	Value
Number of Instances	100
True Positives	53
True Negatives	35
False Positives	8
False Negatives	4
Precision (Positive Predictive Value)	53/61 (0.8688)
Negative Predictive Value	35/39 (0.8974)
Recall (Sensitivity)	53/59 (0.8983)
Specificity (True Negative Rate)	35/43 (0.81395)
F1-score	0.8833
Accuracy	0.8805970149
Mean Squared Error	0.1231766531
Mean Absolute Error	0.1311302226
R2	0.7307089029

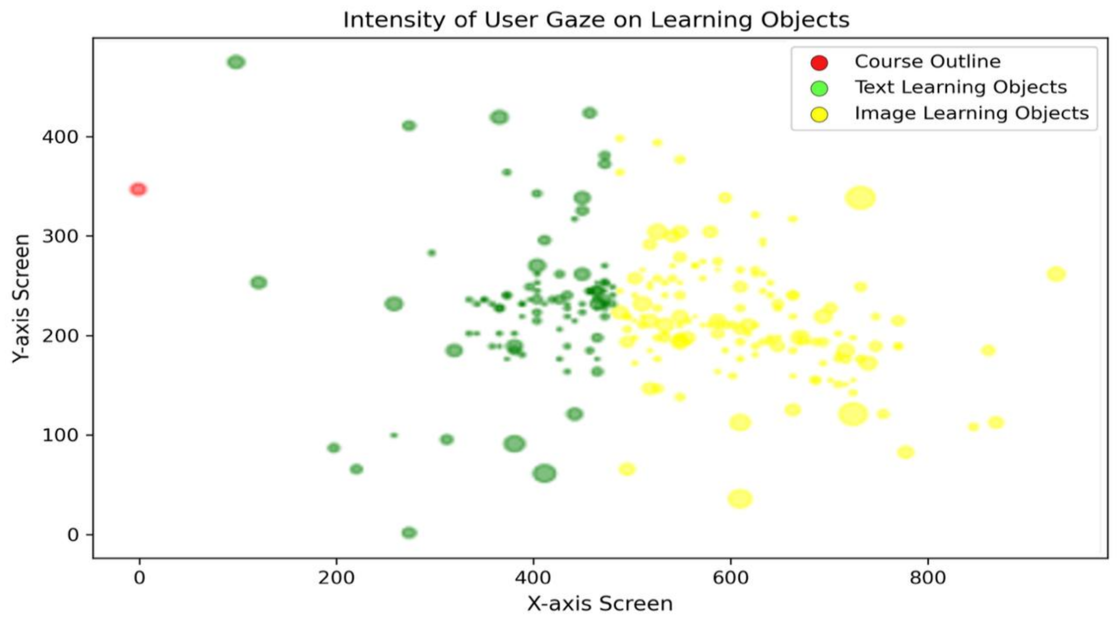

Figure 4. Heatmap showing intensity of user gaze on learning objects in two sides of FSLSM

The effectiveness of the adaptive e-learning platform was evaluated across all four levels of the Kirkpatrick Model to ensure technical and pedagogical success. At level 1(Reaction) is that the study indicated high learner satisfaction, with 75% of learners finding the system's interface engaging and easy to use as shown in Figure 5(a).

Level 2 (Learning) is the survey conducted to assess learners' knowledge acquisition and skill development through pre- and post-tests which showed significant improvement in learners' understanding of the subject matter, with ~92% of the learners stating improved understanding pointing to the system's effectiveness in facilitating knowledge transfer as shown in Figure 5(b).

In the evaluation at Level 3 (Behaviour) as shown in Figure 5(c) indicated that nearly 58% of learners expressed high confidence in their ability to transfer and integrate the newly acquired knowledge into their academic and professional pursuits.

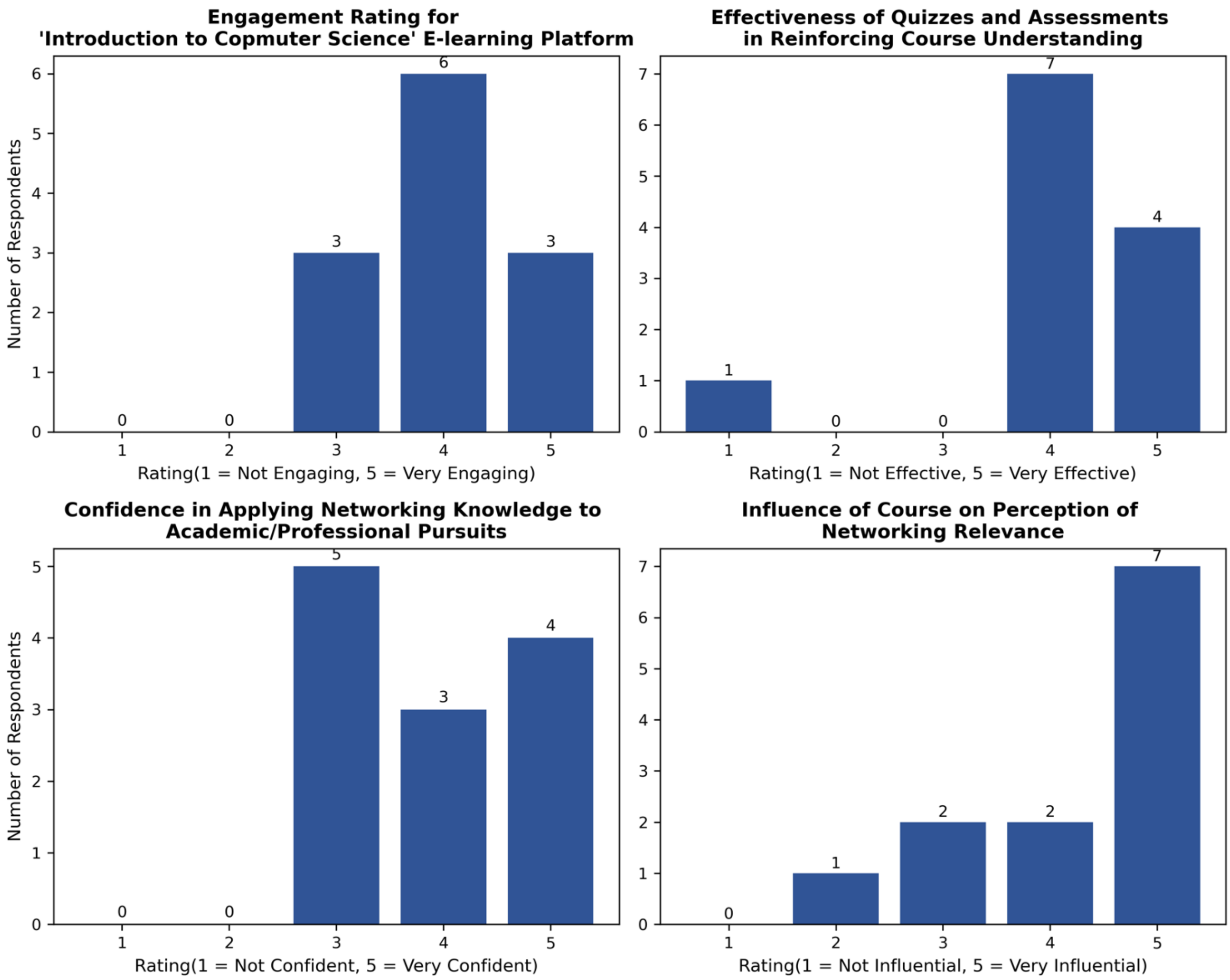

Figure 5. (a) Level 1 Kirkpatrick Model Evaluation – User Reaction via Engagement (b) Level 2 Kirkpatrick Model Evaluation – User Learning via Quiz and Assessments (c) Level 3 Kirkpatrick Model Evaluation – Impact on User Confidence (d) Level 4 Kirkpatrick Model Evaluation – Influence on User Perception

Figure 5(d) shows that Level 4 (Results) confirmed the system's impact, with 75% of learners reporting that the personalized training made the content highly relevant to their overall course of study. This multi-layered evaluation demonstrates that the multi-source approach effectively improves both engagement and knowledge retention.

5. CONCLUSION

E-Learning platforms frequently employ a one-size-fits-all model, offering the same learning experience to every student regardless of differences in prior knowledge, experience, learning preferences, or personal goals. This lack of personalization often leads to reduced engagement, as learners interact with static and non-adaptive content that may not meet their individual needs. As a result, many platforms experience high dropout rates. In addressing this challenge, adaptive and personalized learning approaches have been explored as effective strategies for improving learner engagement, satisfaction, and overall learning outcomes. Hence, this study develops a machine learning model can capture user interactions with learning objects via an eye tracker and an accelerometer and reliably identify user's learning style based on those interactions. The study adopted a hybrid machine learning model known as the Naïve-Bayes Tree (NBTree).

The experimental results demonstrate that integrating multi-sourced biometric data, LMS interaction data and a machine learning model serves as a better alternative to traditional, static self-report questionnaire-based learning style assessments. By achieving an accuracy of 88.06% and an R^2 value of 0.7307, the NBTree model provides empirical evidence validating the premise that physiological and Behavioural signals such as gaze intensity and vertical scroll speed, capture cognitive engagement patterns that are not accessible through questionnaires alone and are better indicators of cognitive activity than self-reported questionnaires. In particular, gaze intensity and dispersion served as highly discriminative features for learning style segmentation, enabling the system to infer how learners explore, interact and process instructional content.

The pedagogical validity of this approach is further reinforced by the Kirkpatrick evaluation, which supports the feasibility of deploying adaptive e-learning platforms that personalize instructional delivery at the level of learning objects pointing to both technical value and educational impact. The high learner satisfaction (Level 1) and strong learning gains (Level 2) indicate that when a system adapts to detected learning styles, it keeps learners continuously engaged, reduces cognitive mismatch, and improves both acquisition and usability of knowledge. The reported confidence in applying learned concepts (Level 3) and perceived relevance to academic goals (Level 4) suggest that ML-driven personalization based on inferred learning styles fosters long-term professional confidence and makes academic content more relevant to the learner's specific career goals.

Collectively, this positions multi-sourced, ML-driven learner modeling as a practical approach towards more responsive and cognitively aligned digital education systems. This suggests that future adaptive E-Learning systems can move beyond simple interface changes and instead provide deep, intelligent interventions such as dynamically adjusting the presentation of content between infographics, text, or interactive simulations in response to a learner's actual cognitive load and engagement levels. By adopting eye-tracking and mouse interaction patterns, such systems can provide a near real-time and non-intrusive modelling of a learner's cognitive activity without the need to interrupt the learning process. This would support the transition from course-centric to learner-centric environments where the system dynamically adjusts to ensure that every individual achieves a high level of comprehension and improved knowledge retention.

Despite its promising performance, several limitations must be addressed to improve the research outcomes. Firstly, the dataset, while informative, is relatively small, comprising only 100 instances and utilizing a non-probabilistic sampling method limited to Computer Science students. This specific demographic may possess technical familiarity that does not reflect the broader, heterogeneous student population.

Secondly, the model currently infers learning styles at an aggregated level rather than within or across learning sessions. As a result, the system faces a cold start problem, requiring a period of initial interaction before learning style can be inferred. Finally, the use of webcam-based eye tracking, while cost-effective and non-intrusive, is more susceptible to environmental noise, such as lighting variations and head movements or eye glasses, which can introduce inconsistencies to the data compared to specialized, high-end sensors.

Future work will extend this approach into a fully dynamic learner model that updates learning style inferences continuously across learning sessions. This will focus on session-level and temporal adaptation, allowing the system to detect shifts in engagement, strategy, and preference as learners interact with new content or contexts. Also, future research should involve larger, more diverse heterogeneous populations and various disciplines to enhance the generalizability of the dataset ensuring that the personalized adaptive framework remains robust and inclusive for all learners. Additionally, the potential for mobile-based m-learning integration should be explored, as front-facing smartphone cameras offer higher granularity for eye tracking, which could further improve the precision of the model in ubiquitous learning environments. This collectively will enable adaptive e-learning systems not only to personalize content, but to learn about the learner over time making instruction delivery progressively more aligned with an individual's evolving cognitive profile.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] Ayoub, O., Fatima E., GAREH, A. H., & Abdellatif, E. (2025). The evolution of e-learning and its challenges in higher education: A theoretical review. https://doi.org/10.5281/ZENODO.14777792

[2] Ismail, A. M. A. (2024). Exploring the Levels of E-Learning Interactivity: A Review of Research Literature. Journal of Ecohumanism, 3(7). https://doi.org/10.62754/joe.v3i7.4693

[3] Kamal, A., & Radhakrishnan, S. (2019). Individual learning preferences based on personality traits in an E-learning scenario. Education and Information Technologies, 24(1), 407–435. https://doi.org/10.1007/s10639-018-9777-4

[4] Klašnja-Milićević, A., Vesin, B., Ivanović, M., Budimac, Z., & Jain, L. C. (2017). Personalization and Adaptation in E-Learning Systems. In A. Klašnja-Milićević, B. Vesin, M. Ivanović, Z. Budimac, & L. C. Jain, E-Learning Systems (Vol. 112, pp. 21–25). Springer International Publishing. https://doi.org/10.1007/978-3-319-41163-7_2

[5] Liyanage, M. P. P., Gunawardena, K. S. L., & Hirakawa, M. (2016). Detecting Learning Styles in Learning Management Systems Using Data Mining. Journal of Information Processing, 24(4), 740–749. https://doi.org/10.2197/ipsjjip.24.740

[6] Vaishali, S. & Dayanand, S.. (2015). Fundamentals of E-Learning Models: A Review. 2, 107–120. https://www.researchgate.net/publication/349917219_Fundamentals_of_E-Learning_Models_A_Review

[7] Imran, M., Almusharraf, N., Ahmed, S., & Mansoor, M. I. (2024). Personalization of E-Learning: Future Trends, Opportunities, and Challenges. International Journal of Interactive Mobile Technologies (iJIM), 18(10), 4–18. https://doi.org/10.3991/ijim.v18i10.47053

[8] Delungahawatta, T., Dunne, S. S., Hyde, S., Halpenny, L., McGrath, D., O'Regan, A., & Dunne, C. P. (2022). Advances in e-learning in undergraduate clinical medicine: A systematic review. BMC Medical Education, 22(1), 711. https://doi.org/10.1186/s12909-022-03773-1

[9] Valentina, A. & Nelly, A.. (2014). The role of e-learning, advantages and disadvantages of its adoption in higher education. Journal of Instructional Technology and Distance Learning, 12(1), 29–42.

[10] Hu, K., & Raman, A. (2024). Systematic literature review on the holistic integration of e-learning in universities: Policy, human, financial, and technical perspectives. Contemporary Educational Technology, 16(2), ep497. https://doi.org/10.30935/cedtech/14287

[11] Adewale, O. S., Agbonifo, O. C., Ibam, E. O., Makinde, A. I., Boyinbode, O. K., Ojokoh, B. A., Olabode, O. Omirin, M. S. and Olatunji, S. O. (2018). Affect-Adaptive Activities in a Personalized Ubiquitous Learning System. International Journal of Learning, Teaching and Educational Research, 17(7), 43–58. https://doi.org/10.26803/ijlter.17.7.3

[12] Anouar, T, M., & Khaldi, M. (Eds.). (2020). Personalization and collaboration in adaptive E-learning. IGI Global. https://doi.org/10.4018/978-1-7998-1492-4

[13] Klašnja-Milićević, A., & Ivanović, M. (2021). E-learning Personalization Systems and Sustainable Education. Sustainability, 13(12), 6713. https://doi.org/10.3390/su13126713

[14] Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H., & Tudorache, P. (2023). Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review. Education Sciences, 13(12), 1216. https://doi.org/10.3390/educsci13121216

[15] El-Bakry, H. M., Saleh, A. A., Asfour, T. T. & Mastorakis, N. E. (2011). A New Adaptive E-Learning Model Based on Learner's Styles. Mathematical Methods and Techniques in Engineering and Environmental Science 440–448. https://www.researchgate.net/publication/281348400_A_New_Adaptive_E-Learning_Model_Based_on_Learner's_Styles

[16] Sweta, S., & Lal, K. (2017). Personalized Adaptive Learner Model in E-Learning System Using FCM and Fuzzy Inference System. International Journal of Fuzzy Systems, 19(4), 1249–1260. https://doi.org/10.1007/s40815-017-0309-y

[17] Vija, V. & Laila, N. (2012). Learner Model's Utilization in the e-Learning Environments. 924, 162–174. https://www.researchgate.net/publication/251483659_Learner_Model's_Utilization_in_the_e-Learning_Environments

[18] Premlatha, K. R., & Geetha, T. V. (2015). Learning content design and learner adaptation for adaptive e-learning environment: A survey. Artificial Intelligence Review, 44(4), 443–465. https://doi.org/10.1007/s10462-015-9432-z

[19] Uddin, M., Ahmed, N., & Mahmood, A. (2017). A Learner Model for Adaptable e-Learning. International Journal of Advanced Computer Science and Applications, 8(6). https://doi.org/10.14569/IJACSA.2017.080618

[20] Sanjabi, T., & Montazer, G. A. (2020). Personalization of E-Learning Environment Using the Kolb's Learning Style Model. 2020 6th International Conference on Web Research (ICWR), 89–92. https://doi.org/10.1109/ICWR49608.2020.9122314

[21] Ngatirin, N. R., & Zainol, Z. (2021). Automatic Detection of Learning Styles: A Decade Review on Data-driven Approaches. Journal of Physics: Conference Series, 1997(1), 012001. https://doi.org/10.1088/1742-6596/1997/1/012001

[22] Lamya, A., Mohamed, E., & Mohamed, K. (2021). Adaptive E-Learning and Scenarization Tools: The Case of Personalization. International Journal of Computer Trends and Technology, 69(6), 28–35. https://doi.org/10.14445/22312803/IJCTT-V69I6P105

[23] Wibirama, S., Sidhawara, A. P., Lukhayu Pritalia, G., & Adji, T. B. (2020). A Survey of Learning Style Detection Method using Eye-Tracking and Machine Learning in Multimedia Learning. 2020 International Symposium on Community-Centric Systems (CcS), 1–6. https://doi.org/10.1109/CcS49175.2020.9231447

[24] Mu, S., Cui, M., & Huang, X. (2020). Multimodal Data Fusion in Learning Analytics: A Systematic Review. Sensors, 20(23), 6856. https://doi.org/10.3390/s20236856

[25] Alhasan, K., Chen, L., & Chen, F. (2018). An Experimental Study of Learning Behaviour in an E-Learning Environment. 2018 IEEE 20th International Conference on High Performance Computing and Communications; IEEE 16th International Conference on Smart City; IEEE 4th International Conference on Data Science and Systems (HPCC/SmartCity/DSS), 1398–1403. https://doi.org/10.1109/HPCC/SmartCity/DSS.2018.00231

[26] Guabassi, I. E., Bousalem, Z., Al Achhab, M., Jellouli, I., & El Mohajir, B. E. (2019). Identifying learning style through eye tracking technology in adaptive learning systems. International Journal of Electrical and Computer Engineering (IJECE), 9(5), 4408. https://doi.org/10.11591/ijece.v9i5.pp4408-4416

[27] Ing., D. S. (2006). Mouse Movement Monitoring in learning style detection. 1–5.

[28] Bittner, D., Hauser, F., Nadimpalli, V. K., Grabinger, L., Staufer, S., & Mottok, J. (2023). Towards Eye Tracking based Learning Style Identification. Proceedings of the 5th European Conference on Software Engineering Education, 138–147. https://doi.org/10.1145/3593663.3593680

[29] Nawaz, F., Ahmed, W., & Khushnood, M. (2022). Kirkpatrick Model and Training Effectiveness: A Meta-Analysis 1982 To 2021. Business & Economic Review, 14(2), 35–56. https://doi.org/10.22547/BER/14.2.2

[30] Rasheed, F., & Wahid, A. (2021). Learning style detection in E-learning systems using machine learning techniques. Expert Systems with Applications, 174, 114774. https://doi.org/10.1016/j.eswa.2021.114774

[31] Graf, S., Viola, S. R., Leo, T., & Kinshuk. (2007). In-Depth Analysis of the Felder-Silverman Learning Style Dimensions. Journal of Research on Technology in Education, 40(1), 79–93. https://doi.org/10.1080/15391523.2007.10782498

[32] Zhang, Z., Li, Z., Liu, H., Cao, T., & Liu, S. (2020). Data-driven Online Learning Engagement Detection via Facial Expression and Mouse Behaviour Recognition Technology. Journal of Educational Computing Research, 58(1), 63–86. https://doi.org/10.1177/0735633119825575

[33] Spada, D., Sánchez-Montañés, M., Paredes, P., Carro, R.M. (2008). Towards Inferring Sequential-Global Dimension of Learning Styles from Mouse Movement Patterns. In: Nejdl, W., Kay, J., Pu, P., Herder, E. (eds) Adaptive Hypermedia and Adaptive Web-Based Systems. AH 2008. Lecture Notes in Computer Science, vol 5149.

Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-70987-9_48

[34] Argunsah, H., Altıntaş, L., & Şahiner, M. (2025). Eye-tracking insights into cognitive strategies, learning styles, and academic outcomes of Turkish medicine students. BMC Medical Education, 25(1), 276. https://doi.org/10.1186/s12909-025-06855-y

[35] Nugrahaningsih, N., Porta, M., & Klasnja-Milicevic, A. (2021). Assessing learning styles through eye tracking for e-learning applications. Computer Science and Information Systems, 18(4), 1287–1309. https://doi.org/10.2298/CSIS201201035N

[36] Luo, Z., & Wang, Y. (2019). Eye-tracking technology in identifying visualizers and verbalizers: Data on eye-movement differences and detection accuracy. Data in Brief, 26, 104447. https://doi.org/10.1016/j.dib.2019.104447

[37] Tsianos, N., Germanakos, P., Lekkas, Z., Mourlas, C., & Samaras, G. (2009). Eye-Tracking Users' Behaviour in Relation to Cognitive Style within an E-learning Environment. 2009 Ninth IEEE International Conference on Advanced Learning Technologies, 329–333. https://doi.org/10.1109/ICALT.2009.110

[38] Anneli, O. (2012). The Tobii I-VT Fixation Filter: Algorithm description. 1–21.