Communication Papers of the 19th Conference on Computer Science and Intelligence Systems (FedCSIS) pp. 1–8
DOI: 10.15439/2024F5253
ISSN 2300-5963 ACSIS, Vol. 41

A VARK learning style-based Recommendation System for Adaptive E-learning

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***Abstract*—Adaptive e-learning provides the best recommendations of learning resources according to the needs of the student, including learning style, knowledge level, personality, and the time they can spend on learning materials. Despite technological advancements, current e-learning platforms often fail to consider individual learning styles and knowledge gaps, leading to less effective learning experiences. This research evaluates the effectiveness of creating an adaptive e-learning system that uses the VARK learning model and a recommendation system to identify learning styles and provide personalized learning experiences to students based on their knowledge gap and learning preference in particular topics. The system first administers a VARK e-questionnaire to determine the student's learning style, followed by a pre-test to assess their knowledge level. Based on these assessments, the system assigns a personalized e-learning path aligned with the student's dominant learning style and addresses knowledge gaps in specific topics. The proposed system is expected to enhance learning experiences by providing personalized educational content that aligns with individual learning style and addresses specific knowledge deficiencies. This approach has the potential to substantially enhance educational outcomes and effectiveness of learning by delivering customized educational experiences that cater to the unique requirements of every student.**

***Index Terms*—adaptive e-learning, VARK learning style, recommendation system.**

I. Introduction

E-LEARNING systems have been gaining a lot of intentions over the past two decades and have experienced a significant increase in use over the last few years due to the pandemic. These mainly web-based systems provide anytime, anywhere, at any pace advantages to learning. This is because e-learning enables students to engage in active learning at any time and from any location, resulting in positive learning outcomes. T. A. el. Galil emphasizes this growth in e-learning stating that: “the e-learning market size has exceeded $315 billion in 2021 and is expected to climb to $400 billion by 2026. In 2021, 27 percent of E.U. citizens aged 16 to 74 years reported participating in online courses and since 2020, 98 percent of universities have moved their classes online.” [1]. These statistics highlight the critical role of e-learning in enhancing contemporary education.

Numerous e-learning platforms, such as Coursera, Udemy, and EdX, offer diverse online learning opportunities [2]. These platforms provide a variety of learning resources, allowing learners to choose the methods that best suit their educational goals. However, it is often mandatory for learners to engage with video content, as most courses require watching videos along with transcripts or additional learning materials [3]. Such platforms assume that all learners are identical in terms of their learning styles, which is not the case for most learners; some might prefer learning through audio or visual aids rather than video.

In the realm of online and electronic education, personalization and adaptive learning are two key features that can improve the educational process. On one hand, personalization has become a critical element in enhancing the learning process. This involves tailoring and customizing the educational content or services to meet the unique needs and learning styles of individuals or groups. This approach supports more effective learning strategies and increases learner engagement. On the other hand, adaptive learning systems learn from each user’s experiences, needs, and preferences. Such adaptive systems are crucial for providing a responsive and customized educational experience that can lead to better learning outcomes.

The increasing recognition of diverse learning preferences among students highlights the need for adaptive e-learning systems customized to individual styles. The VARK model, which categorizes learners into four distant groups as follows: visual, auditory, reading/writing, and kinesthetic modalities. It provides a foundational framework for understanding these preferences. However, existing e-learning platforms often fail to adequately incorporate these distinctions, leading to unsatisfactory learning experiences. By developing a new adaptive e-learning system that leverages the VARK model, we aim to create a more personalized and effective educational environment. This system will dynamically adjust content and instructional methods to match individual learning styles, potentially enhancing learning outcomes and student engagement in diverse educational situations.

The rationale behind adaptive e-learning is supported by educational psychologists who argue and shown evidence that differentiated instruction is a superior option to the traditional “one shoe fits all" method [4], [5]. Differentiated instruction theory states that to teach the learners effectively and efficiently, the tutor must teach and respond according to the differences in the individual, which might be one or all the learner characteristics which include learning styles, cognitive styles, knowledge level, emotional state and other characteristics that effect the process of learning. By embracing these principles, adaptive e-learning systems can provide a more tailored educational experience, accommodating the unique needs of each learner and fostering better educational outcomes.

The proposed system in this study focuses on providing a novel adaptive e-learning system in terms of assisting students by identifying their learning style through VARK assessment and recommending content based on assessments within the system, engaging them in a modified learning pathway. The first step in creating an adaptive environment is often identifying students' learning styles. It has been observed that different students learn to process information using different learning styles. VARK is a learning model proposed by Fleming and Mills that gained popularity in 1992 [6]. This model is used to describe the several ways in which students learn. The VARK learning style model is specifically significant and is simplistic in nature as it focuses only on the content for adaptation.

With the intention of providing a new adaptive e-learning platform to improve the e-learning experience, we have developed a learning system based on the VARK model. This paper is structured as follows: Section II reviews related literature, Section III offers an overview of the system, and Section IV details the design of the system. Section V explains into the technical specifications of our proposed system. The paper ends with a conclusion in Section VI.

II. RELATED WORK AND BACKGROUND

This section reviews papers that investigate adaptive e-learning systems to accommodate various learning styles and recommendation systems, which align with the scope of this study. This is particularly relevant as other learning style models and recommendation systems are often difficult and complex to represent, requiring significant computational resources. To provide a comprehensive overview, Table I has been generated, which presents the common learning styles identified in several studies.

Amaniyan et al. conducted an experiment to examine the impact of personalized learning, tailored to the individual learning styles of nursing students. Approximately 160

TABLE I.

COMMON LEARNING STYLES IN EDUCATION

Learning Style Theory	Main Dimensions	Main Categories	Key Ideas
Dunn and Dunn Model categories [12].	Environmental preferences, Emotional preferences, Sociological preferences, psychological preferences.	– Environmental preferences: Lighting, temperature, noise, seating arrangements, etc. – Emotional preferences: Relaxation, motivation, activity level, etc. – Sociological preferences: Working alone or in groups, teacher, and peer interaction, etc. – Psychological preferences: Visual, auditory, kinesthetic, etc.	Students learn most effectively when their preferred learning styles are accommodated in the learning environment.
Felder-Silverman Model [13], [14].	Sensing/Intuitive, Visual/Verbal, Active/Reflective, Sequential/Global.	– Active/Reflective: Learning by doing and reflecting – Sensing/Intuitive: Learning through observation and understanding patterns – Visual/Verbal: Learning through visual aids or written text. – Sequential/Global: Learning through linear, step-by-step approaches or whole-picture approaches.	Different learners have different strengths and preferences in processing information and interacting with learning materials.
Kolb's Experiential Learning Model [15].	Reflective observation, active experimentation, abstract conceptualization, and concrete experience.	– Assimilators: active experimentation and direct experience. - Divergent: direct experience and critical reflection. - Assimilators: reflective observation and conceptual understanding. - Converges: active experimentation and conceptual understanding.	learning is a process of a four-stage cycle of reflective observation, active experimentation, abstract conceptualization, and concrete experience.
Honey and Mumford's Learning Style Model [16].	Activist, Reflector, Theorist, Pragmatist.	– Activists: Learning by doing and exploring. - Reflectors: Learning by observing and reflecting. – Theorists: Learning by understanding concepts and theories. – Pragmatists: Learning by applying ideas to real-life situations.	Learning styles are influenced by an individual's personality and preferred method of learning.

students had participated in the experiment. It was concluded that learners had a significant improvement when they studied with personalized learning material [7]. Other models are computationally expensive to implement. For instance, the work done by Rasheed and Wahid, used 25 attributes to predict the learning style following the Felder Silverman Learning Style Model (FSLM) of learning styles. Collecting, processing 25 attributes and using a machine learning model, when the number of students increase is computationally expensive [8].

People who are visual learners tend to remember information more effectively, when it is presented to them in the graphical form or pictorial representations. Auditory learners are those who prefer to listen to information that is presented to them verbally. Learners who take notes to learn and perform well on written tests fall into the category of reading and writing. People who are kinesthetic learners tend to learn by doing direct experiments or taking quizzes [9]. Usually, a questionnaire is administered to determine which category of learner the student belongs to. This questionnaire is a learning preference assessment tool that consists of 16 questions with four options to help determine the student's learning style. Zulfiani et al. in their research proved that science students prefer and learn more effectively using the kinesthetic and aural learning styles [10]. Diaz et al. proposed and developed a VARK learning style based adaptive learning system; they assessed on 100 students and concluded that the learning efficiency was improved due to it [11].

Recommendation systems are a key functionality of adaptive e-learning system. There are several approaches to implementing a recommendation system such as fuzzy logic, concept map, hybrid, multi-stage, and rule-based etc. As an example, Segal et al. disuse that content-based filtering is performed based on the similarity of the learning materials to the student's learning preference, topic interest and knowledge in that concept. Also, collaborative filtering uses similarities between users and items, both can be used to recommend learning resources. In e-learning, it can focus on a group of students [18]. Hybrid recommender system use two categories of recommending techniques, by first gathering resources according to users' choices and then filtering using the group preferences [19].

The multi-stage recommendations are a comparatively new concept in recommender systems where the recommendations go through a series of filtering, ranking, and ordering stages [20]. The mentor will keep track of the topic of interest and the materials in a database. Some of the concepts mentioned above are used in the proposed research in Section III to implement an adaptive e-learning environment. Karthika et al. [21] discuss the importance of adaptive e-learning systems that can accommodate the learner's preferences and knowledge levels of learning. Their work presents an intelligent and adaptive e-learning system for a software package that is fuzzy-based using fuzzy concept maps (FCM) and that gives e-learners the relevant domain content based on their knowledge level.

The learner model is used to identify the characteristics of e-learners such as both personal behaviour and the individual's level of knowledge to provide adaptive learning

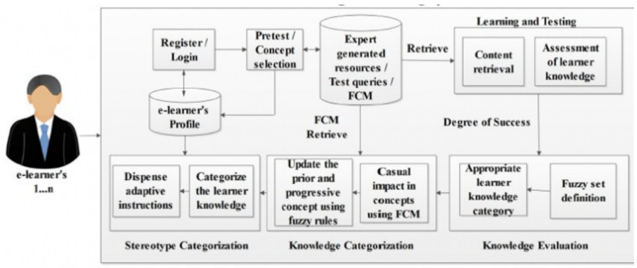

Fig. 1 Intelligent e-learning system [22]

content. These learning resources are maintained in a shared database, and e-learners can retrieve the material they need for learning purposes. Following the learning process, the system provides assessment to assess the e-learner's understanding of the domain concept learned. A fuzzy cognitive map represents the learners' level of knowledge and make proper suggestions for related concepts using fuzzy sets and fuzzy rules. The 26 fuzzy rules help to classify the e-learner's knowledge level accurately.

The system proposed in this work as it appears in figure 1 aims to exceed the constraints that traditional e-learning systems by providing a fuzzy-based intelligent and adaptive e-learning system that can cater to the varying degrees of progress of e-learners. The evaluation of the proposed system shows encouraging outcomes in the accurate categorisation of online learners and their actual knowledge. The proposed system was evaluated only on programming learning material. Nevertheless, they have shown effective results in this domain.

The work of Benhamdi et al. [23] focus on developing a personalized approach to learning by recommending suitable learning materials according to students' prior knowledge, interests, retention abilities and preferences. The approach, known as NPR-EL (New multi-Personalized Recommender for E-learning), mixes content-based filtering with collaborative. The system is incorporated within a learning environment to provide personalised learning resources. The process begins with creating a course by specifying the learning scenario using an xml file called a manifest. The manifest includes elements such as roles, activities, methods, resources, title, and learning objectives. The novel recommender system, NPR-EL, recommends learning materials, which are added to the manifest. These recommended materials, along with the personalized manifest, form a Unit of Learning (UoL).

The approach involves profiling the learners, clustering similar profiles, and predicting ratings for personalized recommendations. A questionnaire is used to gather information on learners' preferences, domain of interest, educational content types, and memory capacity. The questionnaire includes taxonomy and tests of varying difficulty levels. The proposed approach aims to enhance the learning experience by providing personalized recommendations based on individual learners' needs. However, utilizing xml files for the purpose of specifying learning scenarios may have technical limitations and might restrict the adaptability in connecting with other learning management systems.

The work of Esteban et al. [24] offers a hybrid recommendation system (RS) that uses content-based filtering (CBF) with collaborative filtering (CF) to suggest most appropriate courses to students based on student and course details. A Genetic Algorithm (GA) automatically finds the ideal RS configuration that includes the remaining parameters and the primary criterion. Actual data from the University of Cordoba's (Spain) Computer Science Degree, comprising 2500 inputs from 95 students and 63 courses spread over three academic years, was conducted in the experimental study. The findings of the experiment demonstrate a study of the most pertinent course recommendation criteria, the significance of utilizing a hybrid model to boost recommendation reliability by combining student and course data, and superior performance in comparison to earlier models.

Instructors, competencies, knowledge areas, and topics are considered to select the most comparable courses. These metrics may give relevance to each criterion and create a neighbourhood with the most comparable students. The content-based filtering approach calculates a similarity coefficient based on the course content. Additionally, the instructional manuals' contents are indexed to provide another similarity coefficient. The suggested Genetic Algorithm is an adaptation of Eshelman's CHC method, which employs adaptive search techniques to optimize the configuration of the recommendation system, ensuring the best fit for the given data.

The proposed approach is multi-step. Data description and processing come first. Then, the hybrid multi-criteria RS is described. This algorithm provides recommendations for university students regarding their course selection using many student and course factors. Finally, the optimized approach weights each criterion and automatically refines the remaining RS parameters. Using weights, this technique determines criteria significance. Thus, the most crucial factors are weighted higher. The approach also optimizes RS factors like similarity measurements and neighbourhood size. One shortcoming of CF systems is that new students or courses with limited previous data may not receive accurate recommendations, which is a common issue with CF systems.

Various such systems have been developed using machine learning techniques for adaptation in e-learning systems. Many systems use different parameters such as learning style, user preferences, motivation level, and others. The analysis of previous studies has resulted in the development of a proposed system designed to enhance learning outcomes. This system integrates the VARK model with a fuzzy logic and rule-based algorithm to assess and reveal to learners their dominant learning style and areas where they lack knowledge. It aims to deliver a prioritized selection of educational materials in various formats that are tailored to the learners' preferred learning styles. This customization is intended to rectify any misunderstandings in the learners' comprehension and to demonstrate their preferred mode of learning.

III. System Overview

The proposed system focuses on providing an adaptive e-learning environment by understanding the student's learning style and engaging them in a bespoke learning path. This system entitled Flex Learning, is designed to enhance learners' performance, motivation, and engagement by recommending materials aligned with their dominant learning style. The system works as follow; students will be asked to complete a VARK questionnaire shortly after registering with this platform to identify their learning style.

The responses of the students are stored in the database and student profile. Later, the student is asked to check the list of topics they will learn, and a pre-test is performed to determine their knowledge level in those topics. The responses are recorded and classified at this stage too. Based on the previous responses, the recommendation system then ranks the learning content to the students based on their knowledge gap and their preferred learning style. Throughout the learning process, the student's learning is tracked through various tests and level of understanding on the topic.

The architecture of the adaptive e-learning system contains multiple essential components that collaborate effectively to facilitate an individualized educational experience. As demonstrated in figure 2, the system comprises separate components, each specifically designed to effectively engage and provide support to learners. The following sub-sections explore the structure and functionality of these components, showing how they interact in enhancing the learning experience.

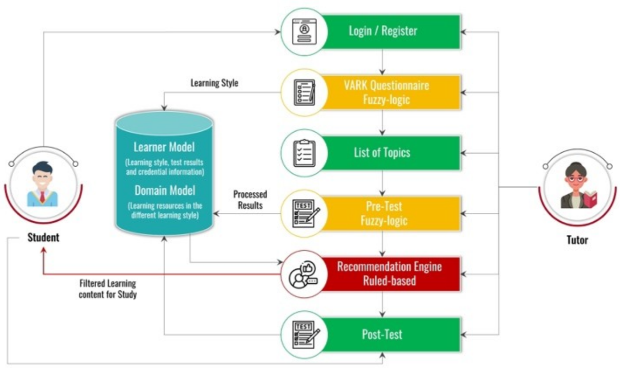

Fig. 2 The architecture of VARK Recommendation System.

A. Login/Register

The learners experience begins with the Login/Register module, which acts as the entry point to their individualized learning journey. In this system, learners can access their own profiles after a successful login, which enables customized educational experience that is aligned with their preferences and learning experiences. Also, the tutor component has administrative ability to generate reports and access to manage all system components and users.

B. VARK Questionnaire

A key component that makes use of the visual, audio, read/write, and kinaesthetic (VARK) learning style framework is the VARK questionnaire. This module provides learners 16 questions to determine their preferred learning method, revealing whether they learn best by visuals, auditory, reading/writing, or hands-on engagement as shown in figure 3. With the help of this essential data, the material distribution strategy is subsequently tailored according to the learner's preferences. The result of the VARK questionnaire identifies the learner's dominant learning style.

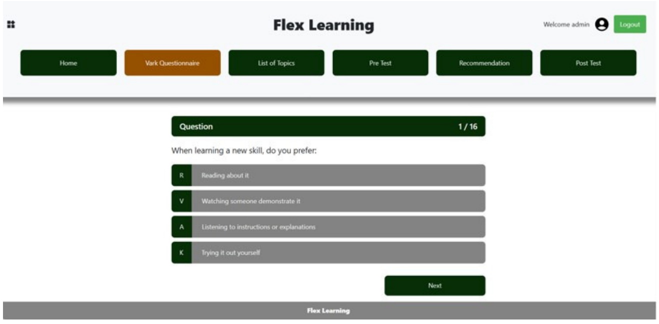

Fig. 3 VARK Assessment Page.

C. List of Topics

The topic list module gives learners the overview of the subjects that are covered on pre-test, and available on the learning system, giving learners responsibility to know what kind of questions they are seen that are covered in the system.

D. Pre-Test Questionnaire

The pre-test evaluates the learner's current understanding of the topics. Its main objective is to identify knowledge gaps and time spent on each question to help prepare the recommendation system for accurate content recommendations in a ranked way. This process works in combination with the learner's dominant learning style identified from the VARK questionnaire, but the pre-test itself does not influence the dominant learning style.

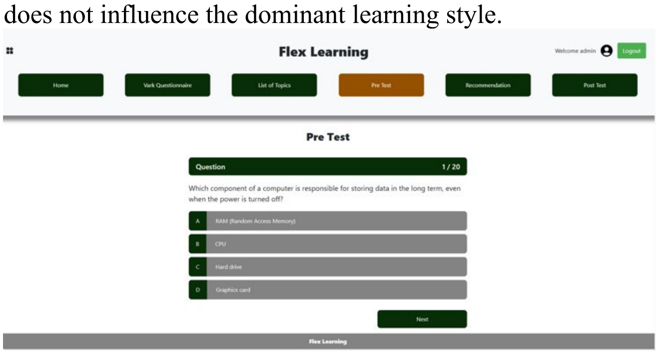

Fig. 4 Pre-Test Page.

E. Recommendation System

The centre of the adaptive e-learning architecture is the recommendation system. It evaluates the learner's VARK dominant learning style, and pre-test performance to rank the materials list for the learner, see figure 5.

F. Content Repository

The content repository contains a collection of educational materials, including texts, videos, chart/diagrams, and quizzes. Moreover, the learner's profile in the repository contains static data that includes important details such as the username, password, email, major, age, gender, and registration number. Conversely, dynamic data includes the

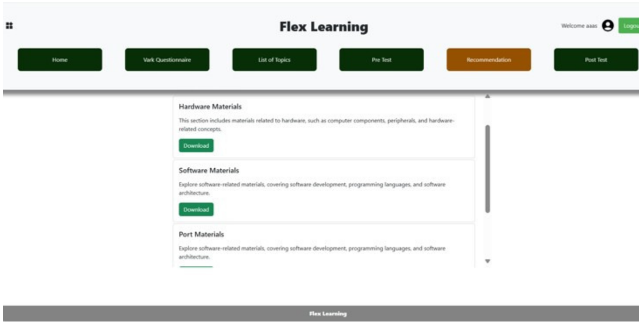

Fig. 5 Recommended Materials Page.

results that are associated with the learner's preferred learning style and learning materials. The relationships shown in figure 6 are indicated by the arrows, which show the direction of the relationship. For example, a user can be associated with one pre-test, one post-test, and one VARK assessment.

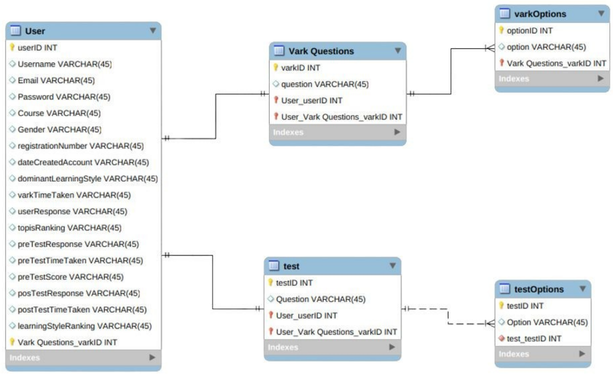

Fig. 6 Flex-Learning Entities Relationship (ER).

G. Post-Test Questionnaire

Upon completing the course materials, the post-test assesses the learner's knowledge retention and comprehension. This assessment, when reviewed with the pre-test results, informs the system's efficacy in content delivery. Learners receive instant results on their performance. See figure 7.

IV. System Design

React is an open-source JavaScript library that is open source which is utilised for developing web applications with many user interfaces. It enables programmers to produce UI

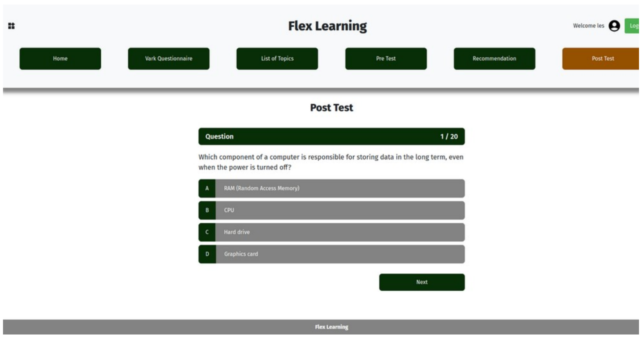

Fig. 7 Post-Test Page.

components that are reusable, which facilitates rapid development processes and improves the user experience through efficient web page presentation [25]. React is known for its high performance, as it updates the user interface without needing to reload the entire web page, leading to faster response times and a smoother client-side experience [26].

A. Frontend (React)

A user interface can be designed through the composition of elements known as components [27]. The front end of a website comprises elements that are visible and interactive to the user, including menus. To create such a frontend web interface, specific tools, and technologies, which are typically a browser-controlled arrangement of HTML, CSS, and JavaScript, are required [28]. The frontend interface was built using React which provides a robust and user-friendly experience. The frontend is designed to help users throughout their learning journey, it guides them through the process, starting from filling out the VARK questionnaire to getting access to tailored resources and tests.

Important elements of the front-end architecture consist of:

1. *VARK Questionnaire:* The questionnaire, which is implemented using React components, allow users finding their dominant learning style between visual, audio, read/write, and kinaesthetic learning modes.
2. *Topic Access*: After completing the questionnaire, users can review the list of topics available in the system. This feature helps learners understand the subjects they will encounter in the pre-test. The interface interaction for accessing topics is built using React component, ensuring a smooth and user-friendly experience.
3. *Pre-test*: The pre-test evaluates the learner's current understanding of the topics. It is designed to identify knowledge gaps, which will inform the subsequent recommendation of learning materials. The pre-test is also implemented with React component, providing an interactive and responsive environment for users.
4. *Recommendations:* Resource recommendations are then assigned to the user based on the user's previous dominant learning style and pre-test performance; it is also aligned based on the user's most failed topic in the pre-test as ranked list.

B. Backend (Node.js)

Node.js is a framework that runs JavaScript on the server side and is designed to manage events. Operating as a single-threaded handle that responds to callbacks and never interferes with the primary thread, Node.js is an exceptionally efficient framework for developing web applications [29]. The backend framework, Node.js, manages data analysis, processing, and front-end communication. The backend architecture is made to handle user profiles and evaluations, analyse user responses from the VARK questionnaire effectively, and provide individualized recommendations through the usage of the fuzzy logic and rule-based algorithm.

Important elements of the backend architecture consist of:

1. *Application programming Interface (API) Endpoints:* The communication of requests and data between the frontend and backend is made via Node.js API endpoints. Receiving user responses from the VARK questionnaire, starting the algorithm to generate recommendations, and sending customised recommendations to the frontend are all handled by APIs.
2. *Algorithm Integration:* The algorithm is integrated into the backend to assess user input and produce tailored recommendations for learning materials. The algorithm is efficiently implemented using Node.js, which considers variables such as learning style preferences and based on learner answers on the pre-test outcomes to generate customised recommendations.
3. *User Profile Management:* Node.js manages user profiles, storing information such as learning preferences, assessment results, and resource interactions. User profile enables the application to reveal VARK result, pre-test, post-test and tracking user time spent on their progress. A personalized learning experience, tracking user progress and adapting recommendations over time.

C. Database (Json file)

JSON is a lightweight data structure that is constructed using the data types supported by the JavaScript programming language. Fundamentally, JSON documents are dictionaries composed of key-value pairings, with the value potentially being another JSON document; this configuration enables an unrestricted number of levels of nesting [30]. The project uses a JSON file to store the data. The data are the extracted by the node server and send through the server endpoint to the Frontend by the API.

V. TECHNICAL DETAILS

The technical implementation of the project involves utilising React for the frontend and Node.js for the backend, along with various libraries to enhance functionality and performance.

A. Frontend (React)

The frontend of our system is meticulously crafted using React, a powerful and flexible JavaScript library for building user interfaces. React's component-based architecture allows for reusable and maintainable code, ensuring a seamless and responsive user experience.

- **Component-Based Architecture**: Reacts component-based architecture allows for modular and reusable UI components, facilitating development and maintenance.
- **State Management**: React's state management capabilities, including hooks such as user state and user context, are utilised to manage application state and facilitate dynamic updates.

- **Routing**: Client-side routing using React router allows users navigate between application components and interfaces.
- **API Interaction**: Fetch APIs are utilised to communicate with the backend, sending requests and receiving responses for data retrieval and manipulation.
- **Styling**: CSS pre-processors such as Sass are used for styling UI components, providing flexibility and maintainability in design implementation.

B. Backend (Node.js)

Our backend, built with Node.js, serves as the robust backbone of the system, handling data processing, business logic, and communication with the database.

- **Express.js Framework**: Node.js uses Express.js as the web application framework, simplifying the creation of robust APIs and handling of HTTP requests.
- **Database Integration**: Json database solution is integrated with Node.js using libraries such as MongoDB Node.js driver for data storage and retrieval.
- **Authentication and Authorisation**: JSON Web Tokens (JWT) is employed for user authentication and authorisation, ensuring secure access to protected resources.
- **Algorithm Implementation**: The algorithm is implemented in Node.js using custom logic and external libraries, enabling analysis of user responses and generation of personalised recommendations.
- **RESTful API Design:** RESTful API design principles are followed to ensure consistency, scalability, and interoperability in communication between the frontend and backend.

C. Recommendation Algorithm

The heart of our system lies in its advanced recommendation algorithm, designed to deliver personalized content tailored to the user's unique preferences and learning style. In this section we provide a general overview of some of the utilized algorithms.

- **Normalization of Scores**: To ensure a fair comparison across different criteria, the algorithm begins by normalizing the VARK, relevance, and difficulty scores of each content item. This step standardizes the scores, bringing them to a common scale for accurate weighted scoring.
- **Ranking of Content**: With weighted scores from the pre-test in hand, the content items are sorted in descending order to prioritize the most relevant items.
- **Filtering Content**: The final recommendation list is filtered to include only those materials that match the user's preferred VARK learning style, ensuring a highly personalized experience.

The recommendation algorithm also includes the initialization of content and data structures, the use of user profile to implement content-based filtering, and personalized ranking as alternative approaches for users. Figure 9 illustrates a general overview of our utilized algorithm through a snapshot of pseudocode.

```
Initialize contentData, content items, title, vark, relevance,
and difficulty attributes
Define userProfile with the user's preferred VARK learning
style
Define criteriaWeights with weights for VARK, relevance, and
difficulty criteria

Function normalizeScores(contentData):
   For each content in contentData:
      If content.vark matches userProfile.vark:
         .....
         .....
      Else:
         ....
         ....
      Normalize content.relevance score
      Normalize content.difficulty score
Return releavance score, difficulty score

Function calculateWeightedScores(contentData,
criteriaWeights):
   For each content in contentData:
      Calculate content.weightedScore using:
         .....
         .....
Function rankContent(contentData):
   Sort contentData
         ....
         ....
   Return sorted contentData

Function recommendContent(contentData, userProfile,
criteriaWeights):
   Call normalizeScores(contentData)
   Call calculateWeightedScores(contentData,
criteriaWeights)
   Get rankedContent by calling rankContent(contentData)
   Filter rankedContent
      .....
   Return filtered rankedContent
```

Fig. 8 A Snapshot of the Pseudocode Utilized in the VARK learning style-based Recommendation system.

D. Deployment and Hosting

- **Platforms for Deployment:** For hosting and scalability, the application in implemented on platforms called AWS.
- **Monitoring and Logging:** Performance tracking, error tracking, and application metrics logging are done via monitoring tools such as New Relic.

The technical details outlined above provide an overview of the frontend and backend implementation, along with deployment considerations to ensure the reliability and security of the system.

VI. Conclusion and Future Work

This study introduces A VARK learning style-based recommendation system for e-learning. This system has specifically developed to evaluate learners, indicate their chosen preferred method of learning and level of knowledge, place them on a learning path, and generate a ranked list of materials for learning to help find gaps in the learners' knowledge. A recommendation system has developed within the system to assess the learner's knowledge level on diverse topics and enhance their performance and entire level of learning. This system includes a pre/post-test component. The VARK learning style questionnaire is utilized to identify the learners' preferred learning style. It then suggests appropriate learning materials based on a ranked concept list that aligns with their preferred learning style.

To evaluate the proposed technology, we intend to conduct a pilot study in an online classroom setting for future research. While previous studies have employed various logical approaches and conducted experiments using different programming languages. The system that is proposed comprises multiple novel features and will go through testing within the subjects of a Computer Science area, involving groups of undergraduate students on first, and second year studying in this field. Also, the study will assess findings using a control group that undergoes the same procedures as previously described in the system overview, but without a customized learning pathway. In this group, students will simply be provided with all pertinent learning materials.

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