Adaptive Educational Hypermedia System for High School Students Based on Learning Styles

Stephen Akuma, Timothy Ndera

Abstract—Information seekers get "lost in hyperspace" due to the voluminous documents updated daily on the internet. Adaptive Hypermedia Systems (AHS) are used to direct learners to their target goals. One of the most common AHS designed to help information seekers to overcome the problem of information overload is the Adaptive Education Hypermedia System (AEHS). However, this paper focuses on AEHS that adopts the learning preference of high school students and deliver learning content according to this preference throughout their learning experience. The research developed a prototype system for predicting students' learning preference from the Visual, Aural, Read-Write and Kinesthetic (VARK) learning style model and adopting the learning content suitable to their preference. The predicting strength of several classifiers was compared and we found Support Vector Machine (SVM) to be more accurate in predicting learning style based on users' preferences.

Keywords—Hypermedia, adaptive education, learning style, lesson content, user profile, prediction, feedback, adaptive hypermedia, learning style.

I. INTRODUCTION

THE significant role of education in high school in building the future of young peers cannot be discounted. However, the panache of delivering this education has varying effects on the outcome and performance of the pupils. Considering the paradigm shift from the traditional learning style, and with the recent COVID-19 pandemic, efforts have been made by researchers to improve online learning. Imagine that content was delivered for high school students according to their preferences, learning styles and interests; such that they are allowed to choose which learning style suits them, this can improve their learning activities [1], [2]. Such personalised information that has been made suitable for each student will make learning more efficient than a "one-size-fits-all" style of education [3], [4]. In the personalised approach, learners can adapt according to preferences such as learning preference, interest or motivation as the case may be [5]. AHS tailor learning towards individual goals and learning styles. Goals and preferences of users are obtained as they interact with the system, and such preferences are used for modelling the users' information needs [3], [4]. Through AHS, tutors are presented with a pedagogical approach that focuses on each learner's needs.

Several adaptive systems have been developed for specific industries like e-commerce, automotive and education aimed

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at reducing the information overload burden on users. In the case of AEHS, learning contents and paths are tailored towards the users, such that it reduces cognitive overload and disorientation while improving learning [5]-[7]. It has two main areas viz, the adaptive presentation which includes frames, fragments, variant pages, flexible text, conditional text, adaptive multimedia, and the adaptive navigation [8]. For this study, we adopt a more dynamic and robust characterization of AEHS that incorporates VARK learning styles to address learners' preferences and dissatisfaction by attempting to customize learning for individual high school students based on their learning styles.

Although AEHS provide the necessary personalisation for learners, the development is quite challenging because of the inherent complexity in the design process, which attempts to harmonise both the educator's and the student's knowledge levels [9]. The other challenge is to design a system with the needed functionality and usability that will take into consideration the different pedagogical teaching approach and learning theories of different users [5]. Research in the development of AHS has been carried out, focusing on the goals and preferences of each user. The researchers are motivated to undertake this work because of the increasing demand for a suitable distance learning management system for high school students during the COVID-19 pandemic which has persisted for several months. The problem with most online learning systems is that they dwell on a single method of delivering learning content to all users, that is, through video lessons irrespective of a student's diverse preference to learning, while this approach is creditable, it is still based on the one-size-fits-all traditional approach of learning. There is therefore a need to develop a learning platform that will adopt students' learning styles for delivering educational content.

Our focus in this research is to model an AEHS that incorporates the VAR learning style to adapt the learning content for high school students, and to present the contents according to their learning preferences. Based on the aforementioned, this research study attempts to answer the question:

- Q1: Can we design an intelligent AEHS capable of performing adaptation for high school students according to learning style?

The remaining part of this research paper is structured as follows: The second section reviews the extant literature, the third section presents the methodology and the architecture of the proposed system, and the fourth section presents the results. The discussion is wrapped in the fifth section, while

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the conclusion and future work is presented afterwards.

II. LITERATURE REVIEW

The design and implementation of adaptive systems are quite different from general software development [10]. Lestari et al. [11] contend that the difference is as a result of the presentation, navigation, adaptivity of the content, navigation facilities and the role of the users. Barria-Pineda et al. [12] also noted that the development of web systems like AEHS is complex, and it needs real-time interaction to personalise contents. AEHS uses an e-learning environment to customize learning content while reducing mental overload problems to enhance adaptivity and efficiency [13]. The aim is to improve learning by meeting every student's information need based on their learning panache [13]

The evolution of AHS began in the 1990s in various application areas, and many systems have been developed with corresponding characteristics, and in some cases, same concepts are reinvented [3], [14]-[16]. Adaptive hypermedia can be divided into three generations - the experimental generation between 1990 and 1996 aimed at provoking innovation, and the subsequent generations which are categorised as the second and third generation became eminent with the increasing number of internet users [17]. Currently, most of the AHS have special and improved features to better learning activities [7].

Until 1996, the research on AHS was still at its infant stage. Only a few independent researchers worked in this area, and the systems developed were not web-based [13], [18]. After the research by Brusilovsky [4], and with the increasing use of the internet, enormous research was carried out in this area, followed by an initial conference 2000. Before 2002, most of the systems developed for learning were Learning Management Systems (LMS). These systems were complex enough to connect teachers and students and to support their interaction [19]. The functionality of the LMS allowed teachers to communicate with their students, to deliver contents through the web, to monitor students' progress, and to give them feedback. As promising as the LMS was, it had its limitation which the AEHS tries to correct. Adaptive systems such as NetCoach, InterBook, and AHA are capable of assisting students to learn better and faster [7]. Others like Adaptive Class Monitoring System enable the teachers to identify weak students [20]. An intelligent technique to solve education problems in AHS was proposed by Tmimi et al. [21]. Our system is similar to the previous hypermedia system. However, we use an intelligent approach to infer users' learning styles.

To personalise educational content to users, education should not be affected by place, time or changing skills, knowledge, preferences and capabilities of the users [16]. This is why it is important and necessary to model user preferences. User modelling is a key feature for personalization as it considers the uniqueness of the user based on their needs [22]. The user model contains user learning styles and other personal information. Efforts have been made by researchers in assimilating learning styles in the design of their adaptive applications [23]. The most significant reason for implementing learning styles in the development of AEHS is because they provide the necessary direction for authoring, using adaptation techniques like navigation path, content adaptation and multiple tools for navigation [24]. The challenging aspect of this is how the learning style can be incorporated in the hypermedia environment. This research attempts to address this by using a question-based intelligent approach as explained in subsequent sections.

Learner's satisfaction can be improved by enhancing the adaptation of content through matching users' learning materials with their learning styles [25]. Though research by Somyürek [20] shows that when the learning style is mismatched with the learning material, it enables the learner to gain experience, figure out his/her learning style and develop a coping strategy to adapt. The research conducted by Mulwa et al. [14] on the ways to determine the learning style of users suggests that users' characteristics like interest, hyperspace experience, background, knowledge and goals differ. This assertion on learning differences was supported by Akuma et al. [26]. To develop an effective personalised system such as AEHS, these individual differences of the users need to be given adequate consideration [7], [16], [26], [27]. Previous research affirms that the performance of users improves if the method of teaching is in line with their learning styles [28]. In our research, we consider it important for learners to have a choice of selecting their learning styles or alternatively, the system suggests it to the learner through the question-based intelligent algorithm. Hence, this research analyses the user profile to detect the user's Learning Styles (LS). We use LS to provide adaptive techniques such as adaptive links and presentation according to user preference similar to Elmabaredy et al. [5] as shown in Fig. 1.
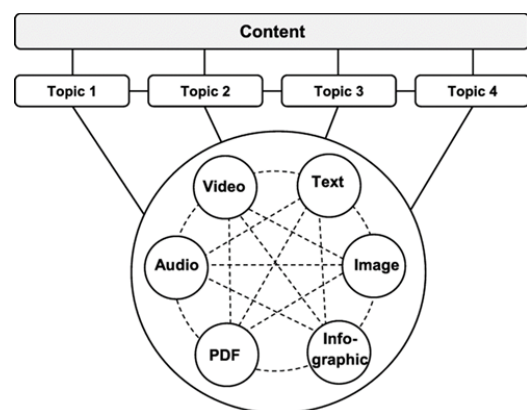

Fig. 1 Multimedia learning style illustration by Elmabaredy et al. [5]

A. VARK Learning Style Model

There is no universally accepted definition of Learning Style (LS). Some researchers see the concept of LS as predictable, stable and unique, while others view LS as the changing nature of an individual over a period [29]. According to Duff [30] LS utilises the psychological, affective and cognitive composite indicators in determining how learners respond and interact to their learning environment. However, a

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definition by Keefe [31] is commonly accepted by researchers. He defines LS as "the composite of characteristic cognitive, affective, and physiological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment". LS is made of three main components: Learning, Instruction Preference and Information Processing [14], and it can be classified in several ways. Apoki et al. [7] described digital content in the form of graphic, video, audio, text as resources that can correspond to the user's LS. One of the methods recently used for classification of LS is the VARK Model developed by Neil Fleming [15] shown in Fig. 2. He classified LS based on preference for kinaesthetic (hands-on activities, experiments, movement), reading and writing (taking notes, reading textbooks, making lists), auditory learning (lectures, discussion, music) and visual learning (diagrams, movies, pictures) [14]. Considering that previous research by Cherry [32] suggests that to improve learning activities, the LS of students need to match the learning content, and due to the simplicity of the VARK model, we adopted and incorporated the VAR LS into our AEHS to group the learners based on their preferences. Our system implements an approach of selecting LS based on the VARK questionnaire which employs intelligence to present content to users.

Fig. 2 VARK LS Model

III. METHODOLOGY AND ARCHITECTURE OF THE PROPOSED SYSTEM

The research approach was secondary and data were collected from secondary sources for the literature review. About forty research papers on AHS and AEHS were reviewed. Several databases like Scopus, Academia.edu, EBSCO, and so on were used to search for resources. The keywords used to perform the search included adaptive systems, adaptation rules and adaptive systems, adaptation rules, pedagogical basis and adaptive systems, LS and adaptive systems, LS, VARK Model, personalization and many others. More so, search journals such as User Modelling and User-Adapted Interaction, Journal of International Review of Research in Open and Distributed Learning, Research and Practice in Technology Enhanced Learning Journal were used. Other sources of information include Encyclopedia of

Information Science and Technology, International Journal for Infonomics (IJI), Computer in Human Behaviour journal, and International Journal of Artificial Intelligence in Education. The procedure for the search and selection was done in two phases. In the first phase, keywords were used to search for articles relating to adaptive educational hypermedia. Articles retrieved from the search process were then screened, such that only articles that are closely related to the research objective were used. In the second phase, we eliminated articles that were not closely related to our research.

A. Proposed LS-AEHS Architecture

The proposed LS-AEHS recommends learning content based on the user LS. Users are required to explicitly state their LS or answer a set of questions based on the VARK learning model. The system then uses an intelligent method to infer the LS of the user from the answers submitted. The proposed architecture is grouped into five main subsystems according to functionality as shown in Fig. 3.
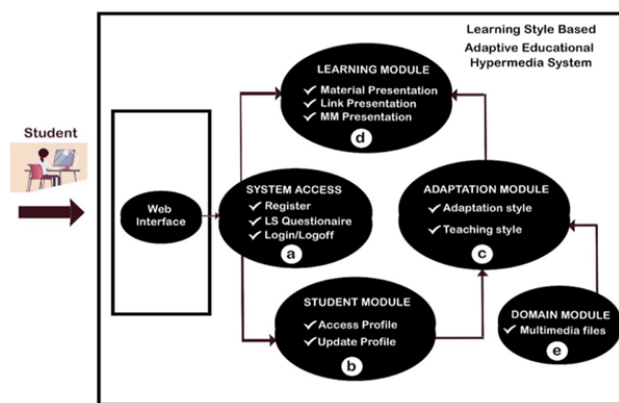

Fig. 3 Architecture of the LS-AEHS

The main subsystem of the LS-AEHS includes System Access, Student Module, Adaptation Module, Learning Module and Domain Module.

a) System Access: This is where users register, log in to have access to the system and log off to leave the system. The LS VARK questionnaire is in this subsystem, learners are presented with questions that are used to infer their LS.

b) Student Model: The student model contains the student's profile. The profile is created when students register to use the system. The profile details include name, LS, grade, personal data and access to learning content. The student's profile is used for the adaptation of learning content.

c) Adaptation Model: This is the subsystem where adaptation takes place. It has Link Adaptation which promotes or restricts new links to the learner; Content Adaptation which provides learners with the most appropriate content; Structural Adaptation which displays the same page content into different structural forms; and Presentational Adaptation which presents the content of the page in different font type, colour and text size. An

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intelligent technique is used here to match the students' LS to their corresponding learning content. In this work, SVM is used for the prediction of the students' LS based on their preferences. The adaptation model links with the domain model to aid adaptation.

d) Learning Module: The learning subsystem is an interface between the student and the adaptive system during learning activities. The learning activities of the students include studying course resources, completing feedback forms, updating the LS and viewing profile. The presentation of hyperlinks to the students in the learning module is dependent on the information derived from the adaptation model. The learning module contains facets like LS and learning history.

e) Domain Model: The domain model contains learning resources in a particular domain. This subsystem houses relevant folders and files containing resources to supply to the Adaptation Model for adaptation. An institution that intends to use this system to deliver content will be required to register teachers who will create files with their course resources.

IV. RESULT

This section presents and discusses the overall performance and functionality of the designed LS-AEHS as it attempts to answer our research question stated earlier. Screenshots from the system were used extensively to depict the resulting process, from the registration of new users and prediction of learning preference to adaptation and presentation of learning content according to the student's profile.

A. User Profile

The system has an interface for the registration of new users and the login page as shown in Fig. 4. After the login, the user is linked to a dashboard containing the students' profile and other details like the subject, topic, feedback form, lesson ID and class ID. This information is used during adaptation. Fig. 5 shows the student dashboard. The student profile is created after the registration and subsequent interaction. The information captured from the user includes LS, grade, personal data and access to learning content. Fig. 6 shows the student's profile page.

Fig. 4 Student Registration page

Fig. 5 Student Dashboard

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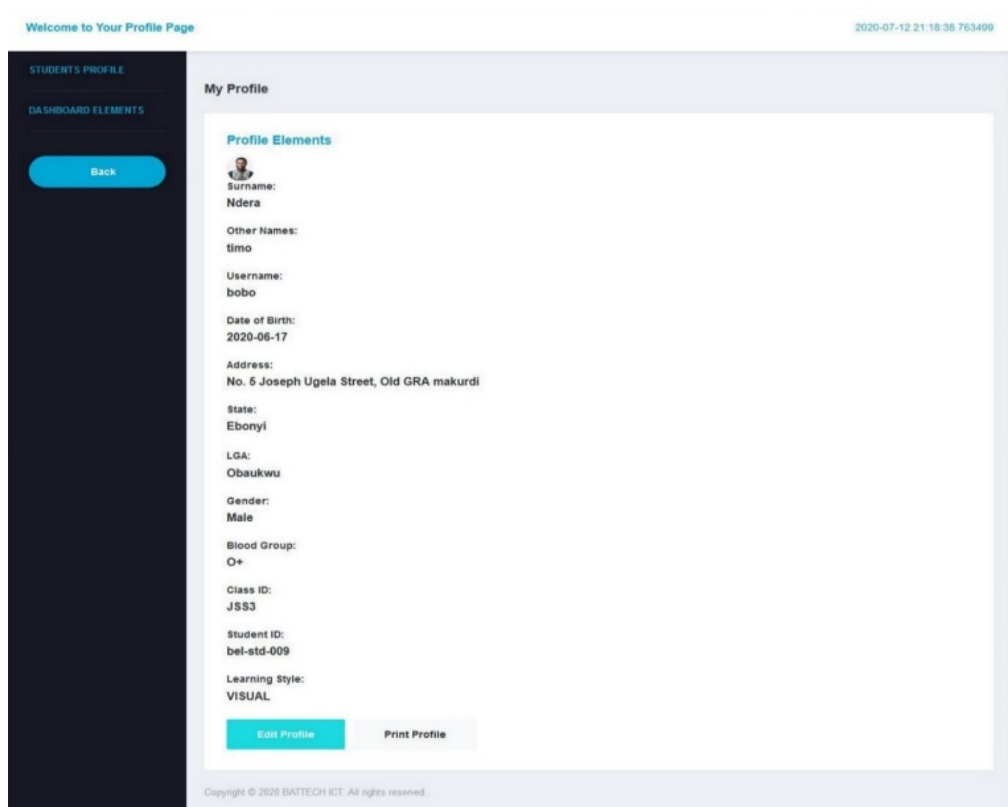Vol:15, No:2, 2021

Fig. 6 Students Profile page

B. Learning Preference Recommendation

After logging in, and clicking the Questionnaire button, the LS questionnaire page pops up for the student to answer a set of questions to aid prediction of their LS according to VARK model (https://vark-learn.com/the-vark-questionnaire/). The submitted answers to the questionnaire are collected into an array and passed to the predictive model for prediction. The predictive model deployed for use on the system to improve recommendation for learning preference is the SVM. It is a highly efficient classifier that uses less computational power to generate a recommendation. The evaluation of the model was carried out using 10-fold cross-validation (70% training and 30% testing) and it produced an accuracy of 96.78%. Its accuracy in making prediction was compared with other classifiers and it produced the highest accuracy in this context of LS recommendation. This informed our decision to make use of the model to improve the recommendation for learning preference. Table I and Fig. 7 show the accuracy measure of different models tested on the system.

TABLE I
ACCURACY OF DIFFERENT MODELS

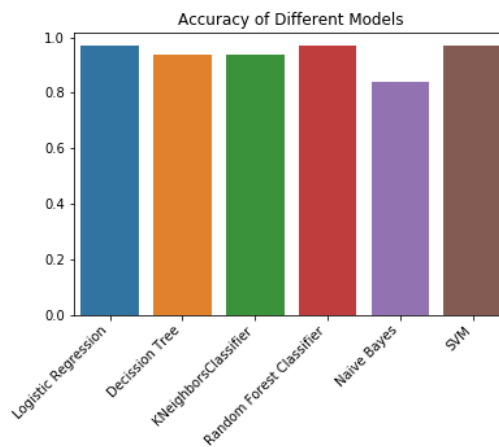| SN	Classifier Model	Accuracy %
1	Naïve Bayesx	83.87%
2	SVM	96.78%
3	Random Forest	96.77%
4	K-Neigbors	93.55%
5	Logistic Regression	96.77%
6	Decision Tree	93.55%

Fig. 7 A Chart representation for the accuracy of models

The prediction returns a VARK LS that infers the student's preference based on the answered VARK questionnaire and SVM classifier as shown in Figs. 8-10. If the system returns [VISUAL], it signifies that the student has a high preference for visual learning and as such, the content will be presented with additional links to multimedia content such as images, maps, diagrams, flowchart, videos, graphs and so on.

If the system returns [AURAL], it shows that the student has a strong preference for aural learning and so learning content will be delivered alongside links to multimedia content like an audio message, music, sounds and so on.

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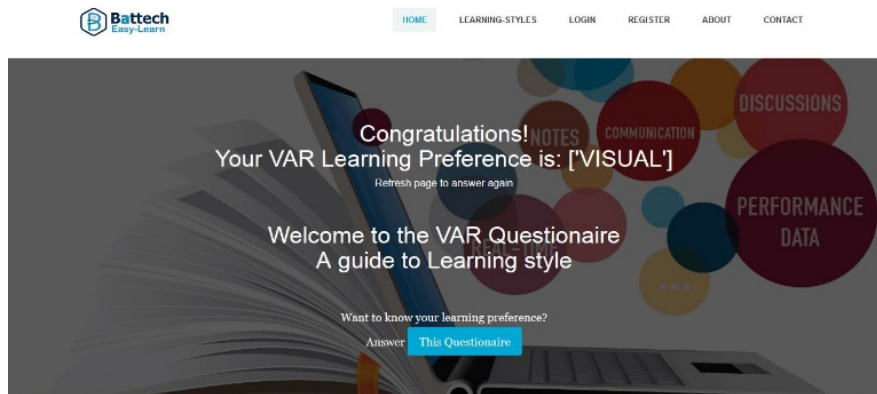Vol:15, No:2, 2021

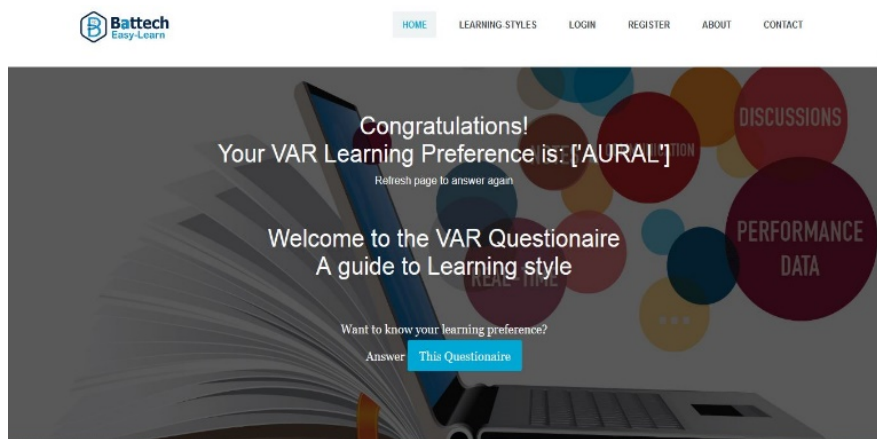Fig. 8 Prediction result for visual preference

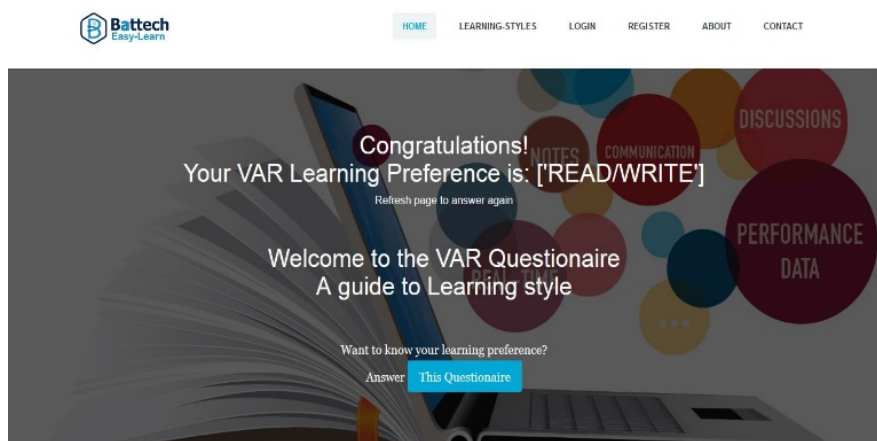Fig. 9 Prediction result for aural preference

Fig. 10 Prediction result for Read/Write preference

If the predicting algorithm returns [READ/WRITE], it means that the student has a strong preference for Read/Write learning, and the content will be delivered with additional links to materials that will be read.

V. DISCUSSION

The VARK learning preference was incorporated into the LS-AEHS to deliver learning content to individual students according to their respective profiles, providing feedback mechanism for each lesson for students to interrelate with their tutors on issues or challenges relating to their lessons. The system also assists tutors in developing more suitable content for students and effective academic planning. Furthermore, the system's ability to accurately make predictions of leaners' preferences from the VARK model as rightly captured in the previous section is another feature that makes the system better than previous AEHS; the algorithm used for this prediction proved to be almost 100% accurate in returning

learners' preferences, better than that reported by Putnam and Conati [33] and Bull and Kay [34].

Selecting a LS for each student is an important part of the system as it leads the system to accurately present content suitable to the selected style, thereby reducing the cognitive overload of the students and improving learning activities. Although the system was not tested with real high school students, its predictability of the LS shows a high level of accuracy. Unlike the traditional LS which is generic, this system uses a LS to enhance personalisation of learning resources.

VI. Conclusion

This research work uses intelligent techniques to match high school students to their LS to improve learning activities. The implemented AEHS has five main modules, the student access module, the student model module, the adaptation module, the learning module and the domain module. It supports the efficient distribution of learning resources based on students' LS. SVM was used for the prediction, and the evaluation of the model was done using 10-fold cross-validation, producing an accuracy of 96.76%. The future work will involve the evaluation of the system with real high school students. A comparative study similar to that of Elmabaredy et al. [5] will be carried out between users of the system and non-users of the system to see if there is a significant difference in their academic performance over time.

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