



Multi-Agent Adaptive e-Learning System Based on Learning Styles

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Abstract

Most traditional e-learning system fails to provide the intelligence that a learner may require during their learning process. Different learners have different learning styles but the current e-learning systems are not able to provide personalized learning. In this paper, we discuss how intelligent agents can aid learners in their learning process. Three agents have been developed namely, learner agent, information agent, and tutor agents that will be integrated into a learning management system (Moodle). Learners are provided with a personalized recommendation based on the learning styles.

Keywords: personalized feedback, Moodle, intelligent agents, learning styles, recommendation.

1. Introduction

Following the advancement of technology, instructors and learners are currently leaning towards e-learning systems/applications for learning purposes. The traditional learning model usually provides a lot of learning materials for all the students despite that they have different learning styles, preferences, and interests (Hosni et al., 2020). Learners have various ways how they learn and acquire knowledge (Balasubramanian & Margret Anouncia, 2018). Some students dwell on data and algorithms, others prefer theories and mathematical models to understand. Some students understand better with pictures, diagrams, and all visual forms, others are better with verbal form and spoken explanations. Besides, some students like to learn actively with groups while others prefer learning individually (Lakkah et al., 2017). Furthermore, individual differences among learners have a significant impact on their learning outcomes. Various researches have indicated that provision of the same learning resources and using the same instructional conditions to all the learners lead to reduced performance without the consideration of the different background features, prior knowledge, and learning outcomes (Wu et al., 2018).

In the physical classroom, the instructors ought to understand the preferences and learning styles of the learners they teach. This might be a very difficult task for them to understand the learning styles of all the students. With the advancement in technology, this is possible in

virtual classrooms through the use of adaptive e-learning systems. For instance, the use of agent technology seems to be the key method for addressing this challenge. The use of intelligent agents makes it possible to achieve a robust system that caters to the needs and the preferences of the students which provides adaptability and intelligence to the e-learning system through the use of the utilization of agents (Nadrljanski et al., 2018).

In this paper, we propose the use of intelligent agents to achieve adaptive learning through the identification of the student learning style using the VARK Learning style model. Adaptive learning will be through the provision of learning materials whereby intelligent agents provide the students with learning materials that match the student’s learning style.

2.0 Literature review

This section reviews literature on the various learning style models, personalized e-learning, adaptive e-learning, some literature on intelligent agents, and also how intelligent agents can support adaptive e-learning.

2.1 Learning style models

Numerous researchers have proposed various meanings of learning styles. For instance, Chick (2016) defined learning style as a way of describing how learners are involved in gathering, sifting through, interpreting, organizing, and coming to conclusions, and storing information for further use. Jaleel and Thomas (2019) define learning style as the concept that people differ regarding what mode of instruction or study is the most effective for them. According to Kumar et al (2017) learning style is the most favorite approach that a learner uses to learn. They also described it as a characterization of attributes, qualities, and preferences that people gather, memorize and execute information.

Numerous learning style models exist that are used by pedagogical experts in the provision of adaptivity in e-learning. Over seventy learning style models exist but the most adopted are the Felder-silver model (Zagulova et al., 2019), Kolb model (McLeod, 2017), Honey-Mumford (Kumar et al., 2017), Myers-Briggs Type Indicator, and the VARK model (Imran Hussain, 2019), as discussed in Table 1 below.

In this paper, we use the VARK model to demonstrate how the learning style of a student can be identified and apply intelligent agents to provide adaptive materials as per the student learning style. We chose the VARK model as the basis for adaptive e-learning because of various reasons. It has been accepted by specialists and is also appropriate for most educational systems. It is also user-friendly and also very easy to understand the results (Daoruang et al., 2018). Furthermore, it is mostly based on the personality type of an individual (Kumar et al., 2017) which suits our case as we are interested in the learning characteristics (learning style) of the students. The VARK model dimensions are described in Table 2.

Table 1. Summary of most adopted learning style models

Learning Style Model	Learning Style Dimensions	Description	Learning Style Instrument
Felder Silverman Model	Active /reflective	Active learners are more inclined towards learning in groups and being correspondent to one another. Reflective learner likes to think and reflect about their ideas. They opt to work on their own and are not excited to learn in correspondence with the other learners.	

	Visual /Verbal	The visual learners remember best what they see, for instance, illustrations, graphs, images, or diagrams. They use the mapping learning idea and usually take shady coding notes. Verbal learner collects more from words and talks clarifications of illustrations and graphs listen to their classmates and takes notes.	Index of Learning Styles (ILS)
	Sequential/global	Sequential learners' study in straight spaces and with consistent little incremental paces to discover arrangements. Global learners are dependent on holistic thinking and bounce to expansive paces. They prefer irregular learning material and, in the process, discover the best way to solve complex problems.	
	Sensory /intuitive	Learning here through sensory or Visual thinking with an orientation towards the facts and concepts in exchange for abstract thinking and orientation towards theory and beyond.	
Kolb model	Converging	A student usually depends on theoretical conceptualization and dynamic experimentation.	Learning Style Inventory (LSI) Revised Inventory
	Diverging	Students focus more on concrete experimentation and reflective perception.	
	Accommodating	Learners focus on concrete experimentation and active experimentation. Prefer performing assignments, plans and getting involved with new thoughts and are great at adjusting to changes in circumstances and taking care of problems intuitively and experimentally.	
	assimilating	Learners prefer abstract conceptualization and reflective perception. They like inducing ideas and hypothesizing models and are more concerned about the thoughts and theoretical ideas than with the individuals and believe that thoughts are intelligently solid than handy.	
Honey & Mumford Model	Activist	They learn by doing and usually have an open-minded method whereby they prefer a diverse task to learn from experience.	LS Questionnaire (LSQ)
	Reflector	They learn intuitively and by watching scenarios. They prefer to study from new experience, analysis and making reports.	
	Theorist	They learn and understand learning resources as per their setting like models, ideas speculations, and certainties while keeping their goals in mind.	
	Pragmatist	They find opportunities for implementing what they have learned and prefer experiments, trying out new ideas and theories from experts.	
Myers Briggs Types Indicator	Perceive/judge	Judging learners are conclusive, arranged, and self-controlled. They concentrate more on completing their tasks/assignments. Perceiving learners are interesting, versatile, and unconstrained. They prefer to begin with assignments to know everything about their undertaking.	Myers Briggs Types Indicator (MBTI)
	Sense/intuitive	Intuitive learners find out examples and also connections among the realities which they have assembled. Sensitive learner favors how they consume data in original universes.	
	Think/feel	They focus on how individuals react to a situation and also how they deal with the external world.	
	Extraversion/introversion	Introversion learners focus on ideas, concepts, and abstractions. Extraversion learners prefer actions and interacting with the others.	
VARK (Visual, Auditory, Read/Write, Kinesthetic)	Visual	Visual learners prefer to use figures, pictures, and symbolic tools such as graphs hierarchies models, and arrows which represent printed information.	VARK Questionnaire
	Auditory	Students prefer to listen rather taking down notes from lectures and engages in a discussion of the taught topics with other students.	

	Read/write	Learners lean toward printed words and text to acquire information.	
	Kinesthetic	Learners learn best by doing. They are inclined more to hands-on experience and preferences not to watch or listen and generally do not do well in the classroom.	

Table 2. VARK model categories/dimensions with the various teaching strategies and learning objects

Learning style dimension	Teaching strategy	Learning object
Visual	Images/diagrams, charts, slides posters, videos, poster, graphs, mind maps	Video PowerPoint slides
Aural/auditory	Topic discussion, talk thoughts, remembering stories, recording notes	Presentation slides with audio, audio videos, and recorded notes
Read/write	Headings and Lists Written notes Definitions and text manuals	PowerPoint slides Text documents
Kinesthetic	Doing practice tests Experimental methods	Practicals Hand on exercise

2.2 Personalized e-learning

Personalized e-learning involves customization of the e-learning so that the specific needs of the learners are met (Pandey, 2017). This personalized e-learning can be provided by determining the basic level options of the learners, managing the various learning styles of the learners (Zagulova et al., 2019), customizing the learning path which has various option include role selection whereby the learner chose the appropriate path instead of having to go through the entire content, through pre-assessments which is determined by the performance of the learner and lastly through surveys thereby a learner choose their area of interest (Pandey, 2017). Personalizing e-learning enables the learners in setting their own goals, setting manageable milestones, selecting their learning path, taking learning at their own pace, selecting the kind of interaction level that they feel is relevant, getting personalized feedback, and using it in assessing their progress and using the recommendation offered to them to enrich their learning (Pandey, 2017).

2.3 Adaptive e-learning

An adaptive system refers to a system that automatically adapts to the learners on the basis of its assumption about the learner. This means that the systems must be flexible to the needs and also the characteristics of the learner (Leka et al., 2016). The key thing to consider when building an adaptive e-learning system is determining which learner characteristics to make adaptive to come closer to the learner demands which is an important factor indicating its success. Various adaptivity parameters are considered when developing adaptive e-learning systems including learner knowledge, learning styles, cognitive abilities, and learning behavior and motivation. Learning resources and adaptive learning are significant in the subject of the learning process of every learner (Diaz et al., 2018)

Adaptive e-learning systems are the new trend in e-learning whose goal involves the personalization of learning material and their sequences in matching the needs of the individual student as close as possible. These systems combine the student features like learning styles, affective state, and knowledge level to provide personalized services and recommend the appropriate learning materials to the student. The main challenge with designing these systems is identifying the student needs or features that need to be adaptive (Leka et al., 2016).

The approach of adaptivity is dependent on the idea that learners can study more effectively provided with the learning materials per their learning style. Many people have different learning styles and thus adaptive e-learning is another form of e-learning that satisfies the needs of each individual in learning. To ensure effective learning for all learners, adapting teaching strategies and content that meet the individual learner is termed as the central and persistent issue in the learning process. In contrast to difficulties in identifying the individual differences in traditional classroom settings, adaptation to different learners is easy in e-learning environments. This is due to the advancement in educational technology through the provision of powerful tools for the implementation of adaptive systems for determining the learners' needs in their learning process (Wu et al., 2018).

2.4 Intelligent agents

Artificial intelligence provides the facilities for the creation of intelligent agents which have intelligent behavior which can act as human whereby each intelligent agent is able to understand its environment by sensors and act upon the environments by actuators (Oskouei et al., 2014). According to Xu, Huang and Heales (2014), an intelligent agent is a program that can accomplish repetitive and expectable missions. Intelligent agents have various characteristics like autonomous, they can learn/reason, they are reactive and goal-oriented, communicate with each other, cooperate and they are mobile as discussed: (i) Autonomous – an intelligent agent senses its environment and act based on its perceive and knowledge obtained from the environment and the rules provided by the designer. This means that each agent has control over the task that is done on their own. (ii) Learn/reason – intelligent agents have the ability to learn experiences and use those experiences in the adoption of their behavior in the environment. (iii) Reactive – Every intelligent agent reacts based on the information that they get from the environment. (iv) Goal-based – intelligent agents have some goals on the basis of the information they have from the environment as it attempts to achieve those goals. (v) Communication – every agent has to interact with the environment for instance humans or other agents to achieve their goals. (vi) Cooperation – when working on complex tasks they need to cooperate with the other agents to increase their abilities in order to achieve their goals and do the task easily. (vii) Mobile – an intelligent agent can navigate with electronic communication networks.

Numerous e-learning platforms do not provide better support thus smartizing these platforms by use of intelligent agents can be a solution to this problem by playing an important role in e-learning (Fasihfar & Rokhsati, 2017). Intelligent agents make a decision automatically without the need for user intervention and also assist users in communicating with computer programs in an efficient manner.

Many researchers find agents as entities that act in a collective manner with other agents thus a multi-agent system is used. A multi-agent system refers to a collection of independent entities which are known as agents that communicates and interacts with each other for the purpose of resolving a problem by completing certain goals. These agents are constantly in communication and are either homogenous or heterogeneous and they may or may not have common goals. The utilization of the multi-agent method in an adaptive e-learning system improves the quality of the learning process through customization of the contents to meet the learners' needs (El Fazazi et al., 2021).

2.5 Intelligent agents and adaptive e-learning

Adaptive e-learning systems focus on the adaptation of the courses to ones' learning characteristics. Many adaptive e-learning systems provide adaptivity at the course level through the generation of adaptive content activities and assessments that satisfies the needs and

preferences of the learners (Kolekar et al., 2019). With the advancement of technology, determining some of the learning features of the students like learning style is made easy. For instance, the use of intelligent agents enables automatic detection of learning styles in adaptive systems that support individual learning and also the provision of customized learning as per the student preferences. This in turn boosts the e-learning process making it easy for them to improve in their learning progress.

Numerous adaptive e-learning frameworks are dependent on multi-agent concepts. Intelligent agent characteristics like autonomous, proactive, and cooperative improve the level of the learning process by customizing the needs of the learners. The use of intelligent agents in intelligent tutoring system is very significant as it brings study environment near to the learners and also bring out the studying aspect of humans than any methods of learning (Alexandru et al., 2015). An adaptive e-learning system includes components that generate a process of teaching and learning that cater to the learners' needs and preferences. It is a challenge to adapt learners' needs in e-learning systems as studying is made easy when a learner is engaged in looking for a solution to real problems, activating acquisition of advanced knowledge and the usage of the currently acquired knowledge to provide a solution to problems and also use it their daily activities. Therefore, the process of gaining the knowledge must be strengthened to include flexibility and understand the needs of the learner (Alexandru et al., 2016).

Intelligent agents can be used to understand and capture the needs of the learners like their knowledge, learning styles, cognitive abilities, and learning behavior and motivation thus enabling the provision of adaptation in the e-learning system. This paper provides an adaptive solution by identifying the learning style of the learner using the VARK model with the help of intelligent agents. The next section discusses the methodology which captures the system architecture and the implementation, prototype testing, and lastly conclusion and future work.

3. Methodology

The study adopted Prometheus methodology because of the nature of the system as well as its rigor it employs for evaluation, concentrated design, and development phase. In relation to the study, the following are the processes adopted in the design of the system as indicated below:

- System specification/problem identification – this phase involved determining the learning style of the students since every learner has different styles when it comes to how they consume information. They also have different preferences and characteristics hence they need to have different approaches when it comes to learning
- Architectural design – Developing three agents including tutor agent, learner agent, and information agent to aid the students in their learning process
- Detailed design and testing phase-this involved determining how the three agents interact and communicate with each other for the appropriate outcome and also integrating them into Moodle to determine their results.

3.1 *The system architecture*

The first step in providing adaptivity is dependent on identifying the learner's style through the VARK model. Once the students login in, they administer the VARK questionnaire to capture the learning style of each learner. The learner should know their responses and the impact of their answers. This is to ensure that there is a guaranteed accurate response in the

questionnaire. The responses are stored in the system which is used to determine the resources that match their learning style. The recommendation of the learning materials to learners is based on their learning style. Adaptive e-learning is upheld through the provision of learning materials that correlate to the learners' goals and their style of learning. Upon the expression of learners learning achievements as well as their learning style, the learner agent will look for the content from the repository/database. For instance, if the student is read/write, the system will recommend to the learner content in a link in form of pdf, presentation slides, textbook, or lecture notes.

Various links (presentation slides lecture notes, videos, slide player) were collected from the web to train the deep neural network which was integrated into the learning agent. A programming course was chosen (C language) whereby four topics including arrays, functions, data types, and control structures were applied to provide data for training.

Our system suggests a multi-agent adaptive learning system depended on the learning style of the student. In the architecture, the three agents are integrated into Moodle backend where the learner information is retrieved from the database. Once the student logs in, they are subjected to the VARK questionnaire where their learning style is captured by the learner agent and then stored in the Moodle database. The tutor agent communicates and interacts with the other agents, i.e., the learner agent and the information agent whereby it coordinates the learning in the system. First, it has the details of the students (student profile) such as the name, user id, and their learning style since it has access to the Moodle database. Once the study student starts learning it check what the students' accesses such as the module/topics uploaded, assignments and forums. It then communicates this information to the learner agent. The learner agent which has been integrated with artificial techniques using deep neural network recommends the most appropriate materials for the student based on their learning style. After the learner agent determines the most appropriate material for the student it communicates this to the tutor agent which in turn communicates this information (recommended materials/resources) to the information agent. The information agent then displays the feedback to the learner through the Moodle user interface.

Below is the system architecture diagram presentation.

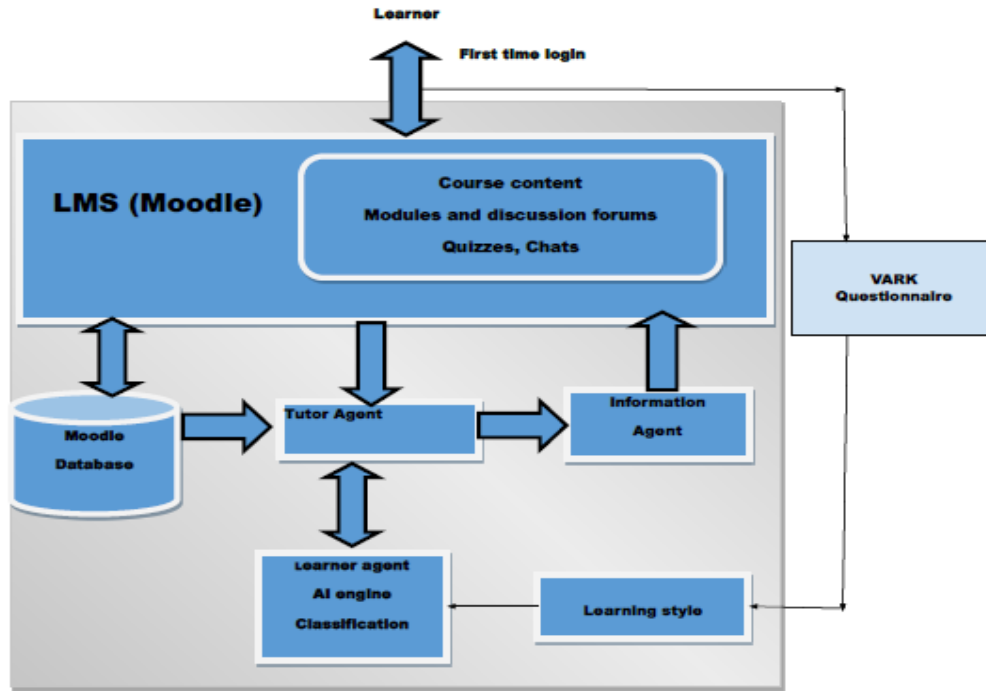


Figure 1. System architecture

The table below summarizes the functions of the various intelligent agents, i.e., the learner agent, tutor agent, and the information agent.

Table 3. Function of the various intelligent agents.

Agent	Function
Learner Agent	Have the AI (Artificial Intelligence) engine that uses deep neural network which helps in the recommendation of the appropriate learning resources to the learners according to their learning style.
Tutor Agent	Coordinates learning in the system. It communicates and interacts with the learner and the information agent. It has access to the Moodle database whereby it has the details of the student (student profile). Tracks the learning process of the student/ activities the student performs in the system and communicate that to the learner agent for recommendation.
Information Agent	Displays the recommended materials to the Moodle user interface which it receives from the tutor agent.

3.2 Implementation

A learning management system (Moodle) is used whereby the existing Moodle database is used which is accessed by the tutor agent. An additional table is added to the Moodle database to store the various learning style of the learners. Once a student login for the first time, they have to administer the VARK questionnaire, if not their first time they are directed to the dashboard. Once they are done answering the questionnaire their learning style is captured and stored in the database. After the capture of the learning style, they are then directed to the content that matches their learning style. For instance, once they access a certain topic like arrays and their learning style is visual, the learner agent checks the most appropriate content from the database and provides the recommendation to the student in a link to a video on that particular topic. The learner agent communicates the video link to the tutor agent which in turn passes it to

the information agent which displays it in the user interface. When answering the questionnaire it can happen that a learner have more than one learning style, but the learner agent picks the learning style with the highest personality score as the learning style.

4. Prototype testing

A course (Introduction to programming in C) is created in Moodle containing four topics as mentioned for testing purposes. Once the user is enrolled for the course for the first time, they first administer the VARK questionnaire as shown below: The questionnaire is administered once when a user login into the system for the first time.

Test Environment

Search Courses

Home Dashboard Events My Courses Hide blocks

Your learning style will be identified shortly. Redirecting...

Your learning style could not be determined. You have been redirected to the questionnaire. Please fill in the questionnaire below to the best of your ability. This is only a one time thing

VARK Questionnaire

Please choose the most suitable choices that describe best the asked question

1. I need to find the way to a shop that a friend has recommended. I would:

- a. find out where the shop is in relation to somewhere I know
- b. ask my friend to tell me the directions
- c. write down the street directions I need to remember
- d. use a map

14. I want to find out about a house or an apartment. Before visiting it I would want:

- a. from somebody who talks it through with me
- b. using a written description of my results
- c. using examples from what I have done

15. I want to find out about a house or an apartment. Before visiting it I would want:

- a. to view a video of the property
- b. a discussion with the owner
- c. a printed description of the rooms and features
- d. a plan showing the rooms and a map of the area

16. I want to assemble a wooden table that came in parts (kitset). I would learn best from:

- a. diagrams showing each stage of the assembly
- b. advice from someone who has done it before
- c. written instructions that came with the parts for the table
- d. watching a video of a person assembling a similar table

Get Personality Score

Figure 2. Sample of the VARK questionnaire

After responding to all the questions in the questionnaire they are notified of their learning style as shown below.

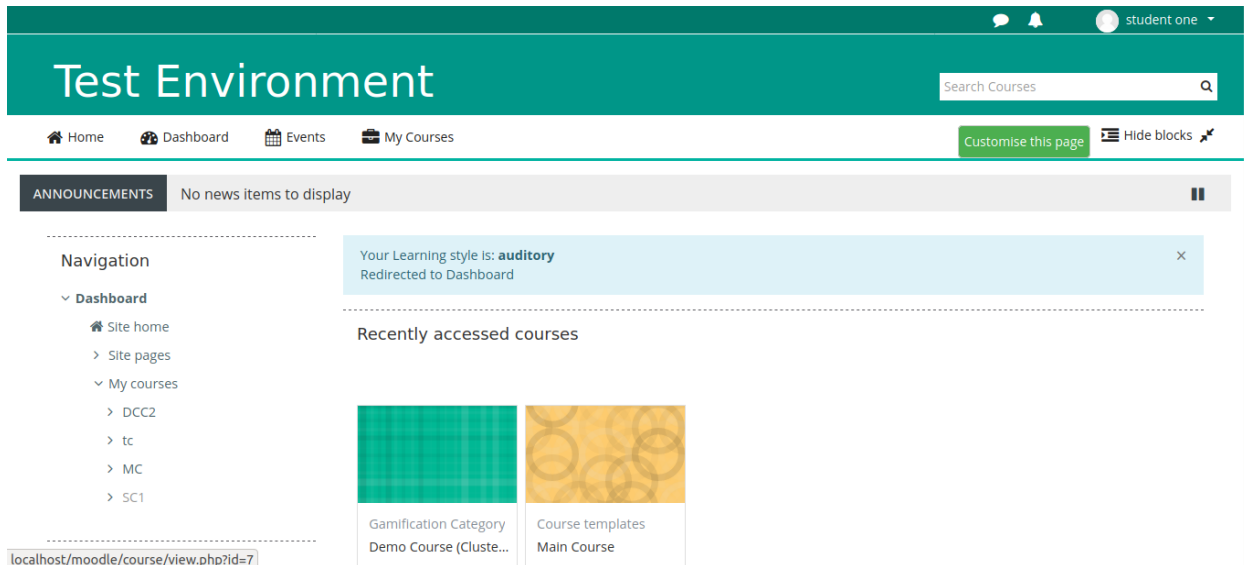


Figure 3. Notification of the learning style

Depending on what they access on the course content, they are recommended materials according to their learning style. For instance, if their learning style is auditory, they will get the recommendation of a link to a video which they can listen to as shown below:

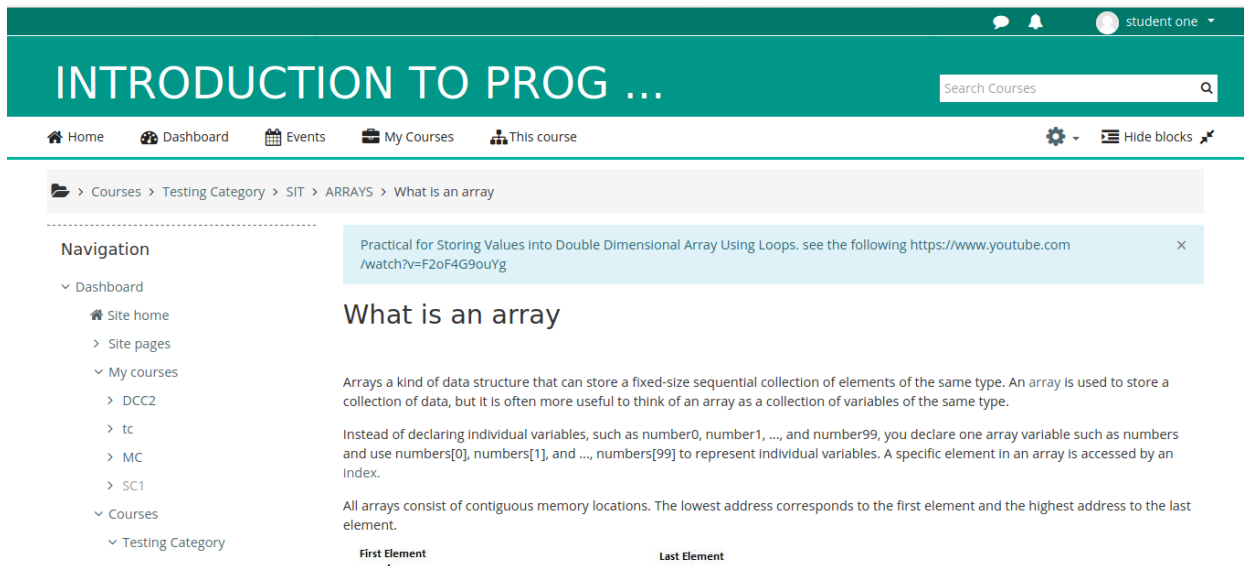


Figure 4. Sample of the feedback /recommendation

5. Conclusion and future work

In this study, we have successfully integrated three learning agents into a learning management system (Moodle) to provide adaptive learning based on the learner's learning style. The learner agent has been trained using deep neural network to learn on how to select the material based on the learning style. This integration allows learners who are using Learning Management System such as Moodle to learn based on their learning style which is more effective than non-adaptive learning.

In the future, other efficient artificial techniques will also be applied to access large datasets for instance from the web where the learners would get the most appropriate learning material as opposed to the ones limited to the repository. In addition, there is a need to apply other learning style models for identifying learning styles such as Felder-Silverman model, Kolb learning style model, or other learning style models and also perform an experimental study on how effective they are in adaptive learning through the use of intelligent agents.

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References

- Alexandru, A., Tîrziu, E., Tudora, E., & Bica, O. (2015). Enhanced education by using intelligent agents in multi-agent adaptive e-Learning systems. *Studies in Informatics and Control*, 24(1), 13-22. <https://doi.org/10.24846/v24i1y201502>
- Alexandru, A., Tîrziu, E., Tudora, E., & Bica, O. (2016). Enhanced education by using intelligent agents in multi-agent adaptive e-Learning systems. *Studies in Informatics and Control*, 24(1), 13-22. <https://doi.org/10.24846/v24i1y201502>
- Balasubramanian, V., & Margret Anouncia, S. (2018). Learning style detection based on cognitive skills to support adaptive learning environment – A reinforcement approach. *Ain Shams Engineering Journal*, 9(4), 895-907. <https://doi.org/10.1016/j.asej.2016.04.012>
- Daoruang, B., Chaichomchuen, S., & Mingkhwan, A. (2018). An adaptive learning system based on proportional VARK to enhance learning achievement concept. *The 4th Joint Symposium on Computational Intelligence (JSCI 4)*.
- Diaz, F. S., Rubilar, T. P., Figueroa, C. C., & Silva, R. M. (2018). An adaptive E-learning platform with VARK learning styles to support the learning of object orientation. *EDUNINE 2018 - 2nd IEEE World Engineering Education Conference: The Role of Professional Associations in Contemporaneous Engineer Careers, Proceedings*. <https://doi.org/10.1109/EDUNINE.2018.8450990>
- El Fazazi, H., Elgarej, M., Qbadou, M., & Mansouri, K. (2021). Design of an adaptive e-learning system based on multi-agent approach and reinforcement learning. *Engineering, Technology & Applied Science Research*, 11(1), 6637-6644. <https://doi.org/10.48084/etasr.3905>
- Fasihfar, Z., & Rokhsati, H. (2017). Study of application of intelligent agents in e-learning systems. *Bull. La Société R. Des Sci. Liège*, 86(February), 398-405.
- Hosni, H., El-Dosuky, M., & Eisa, M. (2020). Virtual learning environment and learning styles. *Journal of Theoretical and Applied Information Technology*, 98(17), 3595-3606.
- Imran Hussain. (2019). Pedagogical implications of VARK Model of Learning. *Journal of Literature, Languages and Linguistics*, 38(November), 33-37.

- Kolekar, S. V., Pai, R. M., & Manohara Pai, M. M. (2019). Rule-based adaptive user interface for adaptive E-learning system. *Education and Information Technologies*, 24(1), 613-641. <https://doi.org/10.1007/s10639-018-9788-1>
- Kumar, A., Singh, N., & Ahuja, N. J. (2017). Learner characteristics based learning style models classification and its implications on teaching. *Int. J. Pure Appl. Math. (IJPAM)*, 118(20), 175-184.
- Lakkah, S. El, Alimam, M. A., & Seghioeur, H. (2017). Adaptive e-learning system based on learning style and ant colony optimization. *2017 Intelligent Systems and Computer Vision, ISCV 2017*. <https://doi.org/10.1109/ISACV.2017.8054963>
- Leka, L., Kika, A., & Greca, S. (2016). Adaptivity in e-learning systems. *RTA-CSIT*, 135-139.
- McLeod, S. (2017). Kolb's learning styles and experiential learning cycle. *Simply Psychology*.
- Nadrljanski, M., Vukić, D., & Nadrljanski, D. (2018). Multi-agent systems in e-learning. *2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics, MIPRO 2018 – Proceedings, October*, 990-995. <https://doi.org/10.23919/MIPRO.2018.8400181>
- Oskouei, R. J., Varzeghani, H. N., & Samadyar, Z. (2014). Intelligent agents: A comprehensive survey. *International Journal of Electronics Communication and Computer Engineering*, 5(August), 2278-4209.
- Pandey, A. (2017). *Benefits of personalisation of elearning*. <https://www.eidesign.net/top-8-benefits-personalisation-elearning/>.
- Wu, C. H., Chen, Y. S., & Chen, T. C. (2018). An Adaptive e-learning system for enhancing learning performance: Based on dynamic scaffolding theory. *Eurasia Journal of Mathematics, Science and Technology Education*, 14(3), 903-913. <https://doi.org/10.12973/ejmste/81061>
- Zagulova, D., Boltunova, V., Katalnikova, S., Prokofyeva, N., & Synytsya, K. (2019). Personalized e-learning: relation between Felder-Silverman model and academic performance. *Applied Computer Systems*, 24(1), 25-31. <https://doi.org/10.2478/acss-2019-0004>

