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The integration of psychology and artificial intelligence in e-learning systems to guide the learning path according to the learner's style and thinking

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ABSTRACT

Traditional e-learning systems fall short in many respects when it comes to delivering content to learners in the most effective way. Research shows that e-learning systems are not accommodative of learners' thinking and learning styles, which leads to poor performance. This paper proposes a way through which this problem can be addressed. The researcher believes that the technology of Artificial Intelligence can be integrated with the learning and thinking styles (Psychology) of learners in an e-learning system to provide an enriched learning experience. No attempts have been made so far to integrate Artificial intelligence and Psychology in an e-learning environment, making this paper unique. The paper explores this subject by designing a system that will be termed a "smart e-learning system." The paper sought to propose Artificial Intelligence algorithms that will be applied to the learning and thinking styles of learners to come up with highly adaptive models for each student that enhances their learning experience. The significant difference in the performance of the control group and experimental group confirms that if psychology and AI are integrated, there is a significant improvement in the student learning experience in an e-learning system. This shows that Artificial Intelligence can work well with Psychology to enhance the learning experience in the e-learning environment.

1. Introduction

The advancement in technology has offered many opportunities for e-learning systems to be highly dynamic and adaptive to the needs of the learner (Tawafak et al., 2019). The evolution of e-learning systems is designed to overcome previous limitations of traditional e-learning systems, avoid information overload, aid students in selecting learning material, and maintain student interest (Rodrigues et al., 2019). This paper uses the same idea to utilize the student model and the technology of Artificial Intelligence to make the system smart. This increases the quality of the learning experience for each student's styles of thinking and learning are built into the learning system, allowing learners to take ownership of the system (Isaias et al., 2017). The technology that is adopted in this research is Artificial intelligence, which will be defined clearly in the coming sections. The researcher believes that when the algorithms of Artificial Intelligence are integrated with one of the most important factors in education; the learning and thinking style of a learner, performance, and experience of students increase. The system automatically classifies learners according to their learning styles and monitors their performance to adjust the way learning is delivered to them. It has been found that when learners' style of thinking and learning; which is defined by Nielsen (2019) as the student model, is built into the education system, students feel comfortable and emotionally rich, which will improve their performance in the class.

Definitions of the word e-learning seem to vary considerably depending on the researcher's goal. "What is e-learning?" (ATD, 2022) argued that there are too many definitions of e-learning and most of which depend on what the researcher is looking for. Global Partnership for Education defines e-learning as a type of learning conducted digitally via

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electronic media, typically involving the internet. The European Commission describes e-learning as the use of multimedia technologies and the internet to increase learning quality through easing access to facilities and services as well as distant exchanges and collaboration. E-learning is learning that is empowered by digital technology (Normadhi et al., 2019). Despite a variety of definitions that are given by scholars, they all agree on two important aspects; the use of technology and the internet.

It is clear from the definitions above that technology plays an integral part in the process of delivering learning experiences to learners. The features and advantages of e-learning can be integrated with algorithms of Artificial Intelligence and psychology in assisting learners by adjusting their learning path based on their performance (Arkorful and Abaidoo, 2015). The paths of learning are defined by the student model of thinking and learning, which produces a rich learning experience. This research paper will call this advanced e-learning system a “smart e-learning system.”

Smart e-learning system customizes e-learning content to enrich learners’ experience and make it more adaptive (El-Sabagh and Yamani, 2020). The customer in this “customization” process is the learner; the recipient of the content. A learner is the most important stakeholder of the education system and by engaging them in learning systems, the systems become more relevant and far enriching. The content of the learning system is delivered based on the learner’s preferred style of learning and thinking (Normadhi et al., 2019). The main concern that prompted the researcher to look into the idea of a smart e-learning system is that the traditional e-learning system exposes learners to the same learning procedure, as though all learners process information the same way (Tirziu and Vrabie, 2015). The learning systems must suit the needs of each learner and their learning styles (Benhamdi et al., 2017). This has been found to produce enriched learning experiences (Hamada and Hassan, 2017).

2. Literature review

This section discusses theories that motivate this research paper. As already introduced, the paper is introducing an advanced system of e-learning that helps learners take a path that is enriching to their learning journey. This system is a result of the integration of Artificial Intelligence and Psychology.

2.1. Psychology

The adoption of a smart e-learning system, which is the main purpose of this research, depends on the strength of the foundational ideas and the validity of the results from the investigation into this issue. The traditional systems of learning share one thing in common, they all treat learners the same (Yassin and Almasri, 2015). They deliver content to learners using the same tools, without considering that each learner has his/her own style of thinking and learning (Kolekar et al., 2017). The argument is that learners have different learning and thinking styles that need to be taken into consideration in their learning journey (Willingham et al., 2015). There is a need, therefore to consider this in a learning system if learners are to get the best experience out of the system (Willingham et al., 2015). Learners’ thinking and learning styles are what Nielsen (2019) called Student Learning Model. He believes that it should be a very significant factor in establishing a learner’s path (Nielsen, 2019).

2.2. The student model

The smart e-learning system developed in this paper is an integration of two fields that are made up of different theories. The first field is Psychology which is made of two theories; the learning style (VARK) (Alkhasawneh et al., 2008) and the thinking style (Raven’s Progressive Matrix) (Raven and Court, 1998). The other field is Artificial Intelligence. This section of the Student Model is going to look at these two theories.

2.3. The learning style model–VARK

VARK is an abbreviation for Visual, Auditory, Reading/Writing, and Kinesthetic (Zhu et al., 2018). This model is illustrated in Table 1.

Table 1: The VARK model

Class	Visual	Auditory	Reading/Writing	Kinesthetic
Techniques	Pictures Movies diagrams	• music • audios • discussions • lectures	• lists • textbook • notes	• movement • experiments • hand-on activities

Fleming and Baume (2006) believed that learners can be classified into four groups, with each group sharing the same learning style (Zhu et al., 2018). Learning style, according to several researchers refers to the process by which a learner organizes, processes, represents, and combines this information and stores it in his cognitive sources, then retrieves the information and experiences in a style that reflects his technique of communicating them (Jaleel and Thomas, 2019). It is argued that a learner can use one or more of the learning styles outlined in the VARK model and if the delivery of content is according to their most dominant style, they will get better quality experience in learning (Jaleel and Thomas, 2019). Fleming and Baume (2006) showed that each class of the VARK model has certain technologies and techniques that when utilized, will provide learners in those classes a rich learning experience.

Fleming and Baume (2006) developed a series of 16 questions, answers to which will result in a learner being assigned to a class. The answers that are provided as options to these questions belong to one of the classes shown in Table 1. It is argued that this list of questions is comprehensive and exhaustive enough to learn enough about a learner's style of learning (Jaleel and Thomas, 2019).

2.4. The thinking style–raven's progressive matrix

The Raven Progressive Matrix as it is known (Wongupparaj et al., 2018), is a scale to measure the abstract reasoning and thinking of participants in a given program. It was developed with the idea that people do not reason the same and by exposing them to the 60 items that are presented to them as a test, the scores can be used to classify participants into different categories (Wongupparaj et al., 2018). This has significant uses in many areas. The researcher believes that it can be used in learning.

When learners are presented with content that is according to their thinking style, they can easily grasp and retain the information, and this in turn will result in higher scores on tests (Nuankaew et al., 2019). The Raven matrix tests the educative ability of a learner, which is the ability to think clearly and make sense of complexity (Wongupparaj et al., 2018). In addition, the matrix also tests the productive ability which is the ability to store and reproduce the information (Wongupparaj et al., 2018). The test consists of 60 items in form of matrices where a learner is required to complete missing parts. The test is termed as progressive as it gets harder as one advance, and this is believed to be one of the best ways to classify learners according to their thinking ability (Wongupparaj et al., 2018).

2.5. Artificial intelligence

Artificial Intelligence is one of the most advanced, if not the best technology in the modern day (Mitić, 2019). IBM defines Artificial Intelligence as a technology that leverages computers and machines to mimic problem-solving and the decision-making capabilities of the human mind (Jarrahi, 2018). Computers have grown the capacity and capability to do many of the things that otherwise could be left for humans to do (Signorelli, 2018). In e-learning, there are tasks that computers can be able to do better in terms of efficiency and accuracy through the utilization of AI algorithms (Mitić, 2019). Though they are programmed by people, the algorithms of AI can learn on their own from what they have been programmed to do. This is called Reinforcement Learning (Sutton and Barto, 2018).

There are many AI algorithms (Casino et al., 2019). That can be used in e-learning, but since the aim of the research is to find smart ways to guide learners along the way, the research focuses on classification algorithms. There are also several classification models that can be employed in this study; however, the researcher decided to use the Naïve Bayes algorithm because of the advantages that are defined in this article. Some of the algorithms include Support Vector Machines (SVM), Decision Tree, Random Forest, Logistic Regression, K-Means, and K Nearest Neighbor (KNN).

Naïve Bayes is one of the Supervised Machine Learning algorithms which is based on the Bayes Theorem. The theorem determines the probability of a hypothesis with prior knowledge. It is naïve because it assumes that the occurrence of a certain feature is independent of other features. Given the aim of the task at hand which is to classify students according to their learning and thinking styles, independence is important. This, therefore, makes Naïve Bayes preferable over other classification models (Zhang, 2017).

It is the aim of this paper to prove that AI and Psychology can be integrated into an e-learning system to guide learners in their learning paths. Therefore, it is important to look at the structure of this Smart e-learning system in Fig. 1.

In the above diagram, a learner is allowed to login into the system as an enrolled student. He will be exposed to a VARK model which is a 16-question questionnaire to determine their learning style. After that, he will be led to Raven's test and the Naïve Bayes algorithm will classify the student according to their choice and scores in the assessment phase. The system assigns students to different classes

3. Methodology

Having developed this smart e-learning system, it was time for the researcher to test the effectiveness of the system. The following hypotheses are what the paper is trying to address:

- Hypotheses 1: Statistical difference:

H0: There is no statistically significant difference between the scores of learners in a conventional e-learning system and learners in a smart e-learning system.
H1: There is a statistically significant difference between the scores of learners in a conventional e-learning system and learners in a smart e-learning system.

- Hypotheses 2: Score improvement:

H0: Smart e-learning system has no effective effect in increasing learner's achievement scores
H1: Smart e-learning system has an effective effect in increasing learner's achievement scores

3.1. Experiment design

This section discusses how the smart e-learning system was deployed to test how effective it is in the delivery of a rich learning experience. The learning experience will be measured by the test scores. This measure has been selected since the researcher is concerned about the overall performance of learners. Fig. 2 is an illustration of the research design process that was taken.

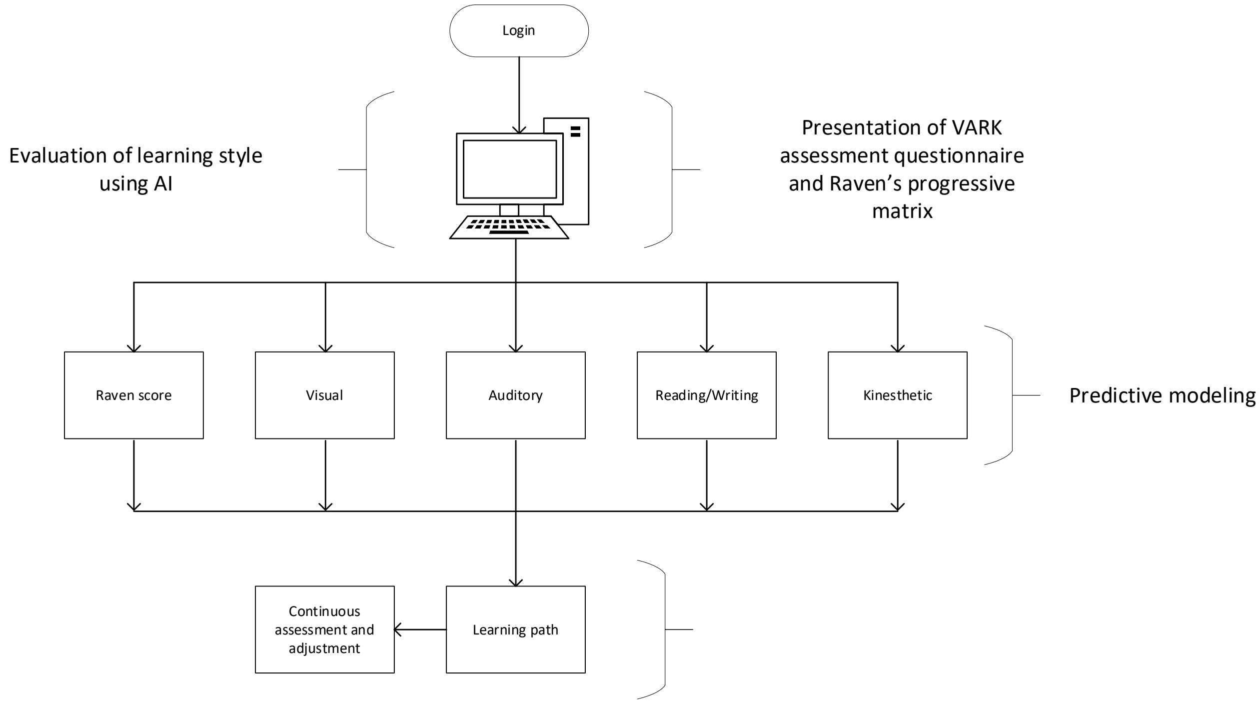

Fig. 1: Integration of psychology and AI

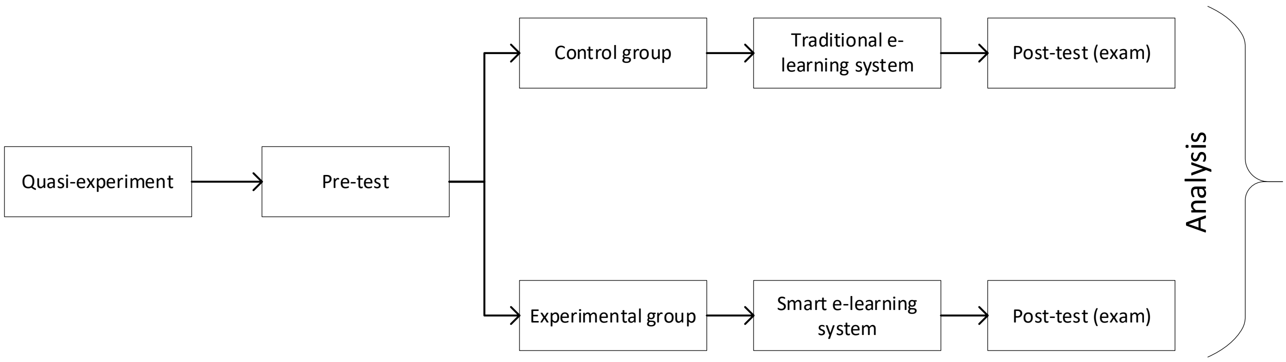

Fig. 2: Research design model

3.2. Research participants

The selection of research participants started with testing a class of 154 first-year students who were studying "Effective Writing for the Social Sciences." The test was to see their basic understanding of the English Language which is the main requirement in the subject. The test was a series of 15 multiple-choice questions on grammar and sentence construction. Results were recorded and the mean score for the test was 92%. It was now time to select a sample that was going to participate in the full-scale study to test the effectiveness of the smart e-learning system.

To choose the sample size that the research was going to use, 4 factors were considered;

- Population size (N) =154
- Required Confidence interval/Margin of error = +/-5%
- Confidence Level = 97%
- Standard Deviation = .5

3.3. Sample description

The final sample consisted of Table 2. Table 2 resulted from the statistical requirements of the researcher. The researcher came up with a sample size of 64. The selection of these participants was based on whether their score for the pre-test fell within 0.5 standard deviation of the mean.

Table 2: Sample composition

Male	Female	Total
36	28	64

3.4. Experimental and control group description

After gaining confidence in the representativeness of the sample, the research moved to the next stage, which is the formation of control and experimental groups. To accomplish this, random sampling was employed with a target of assigning 50% of participants to each group. In Table 3, the sample was split in half to assign 32 participants to the control group and another 32 to the experimental group.

Table 3: Composition of control and experimental groups

	Male	Female	Total
Control Group	19	13	32
Experimental Group	17	15	32

It is clear from the data shown above that there was an imbalance in the sex assigned to each group. However, sex was not an important factor in selecting a sample from the population, but test scores. So this grouping was satisfactory to the researcher, and it was time to begin the experiment.

The content of the experimentation was week 3 of the Effective Writing for the Social Sciences, which was going to be the following week after the experiment. This therefore catered to all possible confounding variables since the content was new to all participants. The content was prepared before the beginning of the semester, and this is what the control group was presented with. They were then given a test at the end of the section to see their performance. However, the experimental group had all factors of the smart e-learning system applied.

The experimental group was exposed to all of the conditions of the smart e-learning system. As shown in the model of the smart e-learning system, the first step is the evaluation of the learner to discover his model. This model is used to effectively deliver content that is of high quality to him. To collect information that was needed for establishing the student's model, the researcher developed a VARK questionnaire which contained 16 questions with their 4 choices that participants needed to select a response from. At the same time, The Raven's test for thinking style was deployed on the computer to classify the students' styles. The responses to these tests were processed by the Naïve Bayes algorithm to place each learner into their categories.

3.5. Validity of the Naïve Bayes

The researcher used this algorithm after a thorough evaluation of its reliability and validity. Cronbach's alpha was used to check the internal consistency and a correlation of 79% was found. According to Hinton (2014), a 0.7 score is regarded as highly reliable. The value of 0.8 was good enough to continue using the tool. So, the data was recorded which was later on used to place participants into different classes. The participants were then placed into different groups depending on their performance on the VARK scale. Table 4 shows the distribution of participants across four classes.

Table 4: Distribution of participants

V	A	R	K	Total
10	9	6	7	32

This shows that most of the participants preferred visuals over other styles.

In addition to the VARK scale which tests the learning style, the researcher placed participants under a second test to evaluate their thinking style. The Raven's Progressive Matrix was adopted in this case. This tests the learner's abstract thinking ability. Since using the entire scale which involves 60 items can need a lot of time and is computationally expensive, the researcher adjusted the scale to include only 15 items.

3.6. Data analysis

This section will draw insights from the data the research gathered. It will show some basic statistics and visual representations of the behavior from the data. The first part will be to look at the statistics of the control group (Table 5). The second part will explore the statistics of the experimental group and the final part will compare the results of both groups (Table 6).

As shown in Fig. 3, the data is normally distributed. As shown in Fig. 4, the score of the experimental group is normally distributed.

a. Control group:
- Sample size (n) = 32
- Male = 16
- Female = 16

b. Experimental group:
- Sample size = 32
- Male = 16
- Female = 16

c. Statistical comparison: This section addresses our statistical hypotheses. The researcher explored data for the groups to compare certain characteristics that are important in answering the research question. Below is the exploratory analysis that was conducted between the two groups.

Table 5: Measure of central tendency

Measure	Score
Count	32
Mean	20.9
Standard Deviation	3.44
Range	16
Variance	11.9

Table 6: Measure of central tendency

Measure	Score
Count	32
Mean	23
Standard Deviation	3
Range	12
Variance	9.15

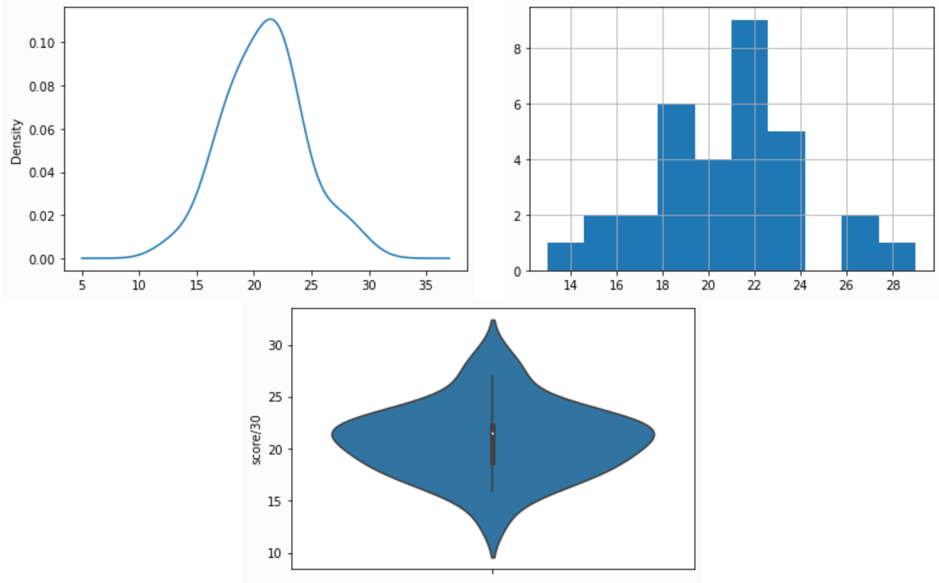

Fig. 3: Distribution of the test score for the control group

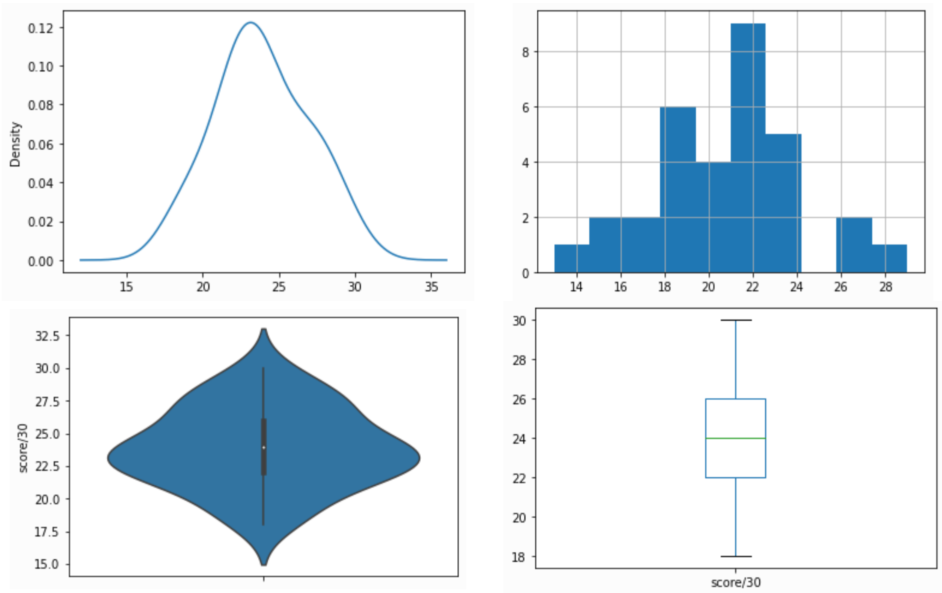

Fig. 4: Distribution of scores for the experimental group

To test the first hypothesis which asks whether there is a significant difference in the achievement scores between traditional e-learning systems and smart e-learning systems, the t-test is employed. The researcher chose this test because it confirms whether the data comes from the same distribution or not. If there is a difference, the significance will be checked by applying a p-value (Table 7). If the p-value is less than 0.05, it will be significant enough to conclude a difference.

Table 7: Test of statistical significance

Group	No.	Mean	Std	t-test	p-value
Control	32	20.9	3.44	-3.703	0.0005
Experiment	32	23	3		

4. Discussion and conclusions

The motivation behind this research was that if e-learning systems consider learners' differences in learning styles and thinking styles and combine them with Artificial Intelligence technology, it will enrich the learning experience and improves the performance of learners. This results from the system's ability to adjust the learning path according to the learner's thinking and learning style. This results from learners being able to take a path that is preferable to them and had been assigned to them in a smart way. The results shown in the preceding section prove this assumption.

As can be seen from Table 7, the p-value is less than 0.05; therefore, the researcher can confirm that there is a significant difference in achievement scores between learners in the traditional e-learning system and learners in the smart e-learning system. In addition, by the comparison of the mean scores between the two groups, considering the conclusion of the first hypothesis, the research can conclude that there is a significant improvement when a smart e-learning system is used as compared to traditional e-learning systems.

There are several advancements that can be looked at to improve this system to make it more effective. There is a need for continuous adjustment of the learner's path to improve their learning experience dynamically. A complex Artificial Intelligence algorithm can be developed which will automatically assess a learner's performance and experience in real time and adjust strategies of content delivery accordingly. In addition, there is a possibility that the content of learning itself can be generated by computer with little to no human interference. This, however, is the next well-advanced stage of the applications of Artificial Intelligence, but one that is not beyond reach.

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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