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An Adaptive Personalized E-Learning Platform With Cognitive Varwk Adaptation And Gamification

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Abstract:

In recent decade, effective and engaging e-learning solutions are imperative, particularly for the early stages of K-12 education. This paper introduces an Artificial Intelligence (AI) approach to e-learning, presenting an adaptive personalized platform that combines Visual/Aural/Read/Write/ Kinesthetic (VARWK) presentation, exercises difficulty scaffolding through skipping/hiding/ reattempting and gamification elements. The platform employs cognitive, behavioral, and affective adaptation techniques to develop a dynamic learner model, effectively identifying and correcting learning style and cognitive level. The adaptation targets encompass adaptive content presentation (VARWK and gamification), exercises navigation, and feedback. To realize its objectives, the platform utilizes Deep Residual Network Learning (DRNL) and an online rule-based decision-making framework. The platform features a front-end dedicated website interfacing with back-end adaptation algorithms. A experiment are conducted on various grades with English curriculum demonstrates improved learning effectiveness, as evidenced by a comparison between post-test and pre-test results. Both groups of students experienced enhancements in academic performance and satisfaction levels, with the VARK group showing slightly greater improvement and higher satisfaction due to the engaging interactive activities and games in the kinesthetic presentation, while maintaining accessibility to other presentation styles when needed.

Keywords: E-Learning, Adaptive Personalization, VARK Presentation, Gamification, Cognitive Adaptation.

1. Introduction

In the past decade, the importance of effective and engaging e-learning solutions has grown exponentially, driven in part by unprecedented challenges such as the COVID-19 pandemic. These challenges have underscored the critical need for innovative educational platforms, especially at the early stages of K-12 education [1].

Traditional educational systems often struggle to accommodate diverse learning styles and cognitive levels among students. The one-size-fits-all approach can lead to disengagement, reduced learning outcomes, and frustration for both educators and learners. The rapid advancement of technology, particularly AI, offers a promising solution to address these challenges and enhance the educational experience [2].

Several challenges stand in the way of creating effective e-learning solutions for K-12 education: Students have varying preferences for how they absorb and retain information, including visual, aural, read/write, and kinesthetic approaches. Adapting to these styles is essential for engagement and comprehension [3]. Students progress at different rates and have different levels of proficiency in various subjects. A system must adapt to each student cognitive level and provide appropriate learning materials and exercises [4]. Keeping students motivated and engaged in the learning process is a constant challenge. Gamification can offer an effective solution to maintain interest and enthusiasm [5].

The problem this paper addresses is the development of an adaptive personalized e-learning platform that overcomes the challenges mentioned above. This platform must not only offer VARWK presentation styles but also dynamically adjust the content, exercises, and feedback to match individual learning preferences and cognitive levels.

The primary objectives of this paper are as follows: to develop an adaptive personalized e-learning platform that integrates VARWK presentation styles, exercises difficulty scaffolding, and gamification elements. To implement cognitive, behavioral, and affective adaptation techniques to create a dynamic learner model capable of identifying and correcting learning styles and cognitive levels. To provide adaptive content presentation (VARWK and gamification), exercises navigation, and feedback to enhance the learning experience.

This novelty lies in its holistic approach to e-learning, combining VARWK presentation styles, gamification, and cognitive adaptation within a single platform. By leveraging AI techniques, such as Deep Residual Network Learning (DRNL) and rule-based decision-making, the platform offers a dynamic and personalized learning experience. The integration of gamification elements ensures sustained engagement.

2. Related works

In [6], the authors introduces the VARK model (Visual, Aural, Read/Write, and Kinesthetic) as a framework for understanding individual learning preferences. It lays the foundation for adapting e-learning content to various learning styles, which is relevant to the proposed platform.

In [7], the research provides insights into the architectural design of adaptive learning systems and their implementation in web-based platforms (WBP). It discusses the importance of cognitive adaptation and how it can improve the effectiveness of e-learning.

In [8], the authors explores the impact of gamification on teaching and learning. It highlights the potential benefits of incorporating gamification elements into educational platforms, which aligns with the proposed platform use of gamification.

In [9], the authors introduces Deep learning, a breakthrough in deep learning. CNN have significant implications for the proposed platform, as they are mentioned as a key technology for learning adaptation.

In [10], the authors explores the concept of adaptive educational hypermedia, emphasizing the importance of adapting content, navigation, and feedback to individual learners. It provides valuable insights into the adaptive elements proposed for the e-learning platform.

In [11], the authors discusses the current state of adaptive learning systems, emphasizing the use of rule-based decision-making and personalized learning paths. It sheds light on the practical implementation of adaptive systems, which is relevant to the proposed platform architecture.

These works collectively provide a foundation for understanding the key concepts and technologies related to adaptive e-learning platforms, cognitive adaptation, and gamification in education, which are central to the research and development of the platform described in your paper.

3. Proposed Method

The proposed method described in your paper outlines the development of an adaptive personalized e-learning platform that aims to enhance the learning experience, particularly in the early stages of K-12 education. The key components and processes of the proposed method is illustrated in Figure 1.

3.1. Adaptive Personalization:

The foundation of the platform lies in its adaptive personalization capabilities. It seeks to tailor the learning experience to individual students, recognizing that students have diverse learning styles and cognitive levels. The platform incorporates the VARK model, which stands for Visual, Aural, Read/Write, and Kinesthetic learning styles. This means that it caters to different ways in which students prefer to learn, ensuring that content is presented in a manner that aligns with their preferences.

The VARWK presentation approach, which stands for Visual, Aural, Read/Write, and Kinesthetic, is a framework for accommodating different learning styles in educational content delivery. It recognizes that individuals have varying preferences for how they best absorb and retain information. While VARWK is a descriptive framework rather than a mathematical one, it can be represented conceptually to explain how it caters to different learning styles.

Visual (V): Visual learners prefer to learn through images, graphs, charts, and visual aids. They understand information better when it is presented graphically. For visual learners, educational content might include: Equations with visual representations, such as graphs or diagrams, Infographics and charts to illustrate concepts and Educational videos or animations that use visual cues.

Aural (A): Aural learners prefer auditory information. They learn best through lectures, discussions, and listening to explanations. Educational content for aural learners might include: Audio recordings of lectures or explanations, Podcast-style lessons and Interactive quizzes with spoken instructions.

Read/Write (R): Read/write learners are most comfortable with written or textual information. They excel in traditional classroom settings, taking notes and reading textbooks. Educational content for read/write learners could include: Textbooks and written materials, Lecture notes and slides and written assignments and assessments.

Kinesthetic (K): Kinesthetic learners learn best through hands-on experiences and physical activities. They prefer interactive learning methods. Educational content for kinesthetic learners might include: Interactive simulations or experiments, Hands-on activities and projects and Physical models or manipulatives.

Gamification Elements: Gamification elements are integrated into the platform to keep students engaged and motivated. Gamified elements, such as interactive activities and games, are designed to make the learning experience more enjoyable and interactive.

Exercises Difficulty Scaffolding: The platform dynamically adjusts the difficulty level of exercises based on individual student performance. This scaffolding approach involves features like skipping, hiding, and reattempting exercises to ensure that students are neither overwhelmed nor bored by content that is too easy or too challenging.

Cognitive Adaptation: To achieve effective personalization, the platform employs cognitive adaptation techniques. This involves continuously monitoring each student cognitive level and learning progress. If a student is struggling with a particular concept, the platform can provide additional resources or adapt the content to better suit their current level of understanding.

Algorithm: Adaptive Personalized E Learning Platform

Inputs:

Student learning preferences (VARWK)

Initial student cognitive level

Learning materials (text, visuals, audio, interactive elements)

Initial exercise difficulty

Outputs:
Adapted learning materials
Adapted exercise difficulty
Feedback and guidance for the student

1. Initialize the student learning preferences (VARWK) based on an assessment or previous interactions.
2. Set the initial cognitive level of the student based on assessments or prior performance.
3. Present learning materials according to the student learning preferences:
   For Visual (V) learners, provide visuals, graphs, and images.
   For Aural (A) learners, offer audio explanations and discussions.
   For Read/Write (R) learners, provide textual content, lecture notes, and written assignments.
   For Kinesthetic (K) learners, incorporate interactive simulations, hands on activities, or physical models.
4. Integrate gamification elements to keep the student engaged:
   Include interactive activities and games that align with the learning materials.
   Track the student progress and achievements within the gamified elements.
5. Monitor the student performance and progress throughout the learning process.
6. Implement exercises difficulty scaffolding:
   Assess the student performance on exercises and assignments.
   If the student struggles, offer hints or additional explanations.
   If the student excels, increase the difficulty of subsequent exercises.
7. Continuously adapt the cognitive level:
   Assess the student understanding and performance.
   If the student demonstrates mastery, advance to more complex topics.
   If the student struggles, provide additional resources or review materials at a suitable level.
8. Provide adaptive feedback and guidance:
   Offer real time feedback on exercises and assignments.
   Suggest supplementary resources or alternative learning paths when needed.
   Encourage the student progress and achievements through gamified elements.
9. Repeat the adaptive process iteratively as the student continues their learning journey.
10. Regularly assess and update the student learning preferences and cognitive level to ensure ongoing personalization.

3.2. Deep Residual Network Learning (DRNL)

The platform utilizes Deep Residual Network Learning (ResNets), a state-of-the-art deep learning technique, to process and analyze student data. ResNets are used for tasks such as identifying learning patterns and optimizing content delivery. A rule-based decision-making framework is implemented to make real-time decisions regarding content presentation, exercises, and feedback. This ensures that the platform can adapt quickly to each student evolving needs. They use skip connections (or residual connections) to pass information from one layer to another. The output of the residual block is given by:

$H(x) = F(x) + x$

where,

$H(x)$ represent the output of a residual block for input x.

$F(x)$ represent the mapping to be learned by a residual block.

In e-learning platform, Input x could be the student data, such as their performance on exercises and their current learning progress. F(x) represents the learned mapping within the ResNet, which helps identify learning patterns and adapt content delivery. H(x) is the output, which could represent a prediction of the student future performance or an assessment of their learning state.

A rule-based decision-making framework involves defining a set of rules or conditions that guide the platform actions in real-time. These rules are based on domain-specific knowledge and can be represented in the form of conditional statements. Let consider a simple rule-based decision for adapting exercise difficulty:

```
If (Student_performance < Threshold):
   Increase_exercise_difficulty
Else:
   Maintain_exercise_difficulty
```

In this rule-based decision:

Student_performance represents the student performance on previous exercises.

Threshold is a predefined threshold value that determines whether the student is struggling.

Increase_exercise_difficulty and Maintain_exercise_difficulty are actions taken by the platform based on the student performance.

Similarly, rule-based decisions can be defined for content presentation, feedback generation, and other aspects of the e-learning platform. ResNets and rule-based decision-making are integrated into the platform architecture to work together. ResNets process and analyze student data to identify learning patterns, while the rule-based system makes real-time decisions based on these patterns and the student current needs.

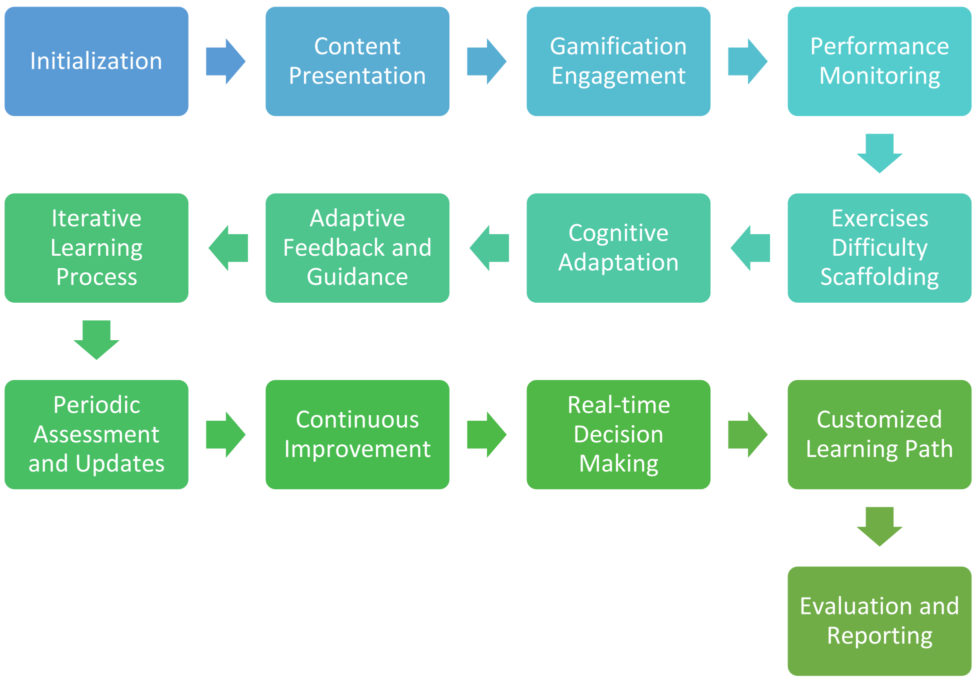

Figure 1: Proposed Framework

4. Performance Evaluation

To validate the effectiveness of the platform, a pilot experiment is conducted with students from various grade levels, focusing on the English curriculum. The results of this experiment are used to assess the impact of the platform on academic performance and student satisfaction.

Experimental Setup:

Parameter	**Value**
Learning Platform	Adaptive E-Learning Platform
Experiment Duration	8 weeks
Grade Levels Tested	English Curriculum (Grade 1 - 10)

Number of Students	100
Learning Materials	English language textbooks
Content Presentation	VARWK
Gamification Elements	Interactive quizzes, games
Cognitive Adaptation	DRNL
Decision Framework	Rule-based decision-making
Exercises Difficulty Scaffolding	Adaptive difficulty levels
Assessment Tools	Pre-test and post-test

Performance Metrics:

- **Academic Performance:** This metric assesses how well students have learned and retained the material. It is typically measured by comparing the scores of pre-tests and post-tests. The formula for calculating academic performance improvement can be:

  Academic Performance Improvement (%) = ((Post-Test Score - Pre-Test Score) / Pre-Test Score) * 100

- **Satisfaction Level:** Satisfaction level reflects students' overall satisfaction with the e-learning platform, including its usability, engagement, and effectiveness. It can be measured through surveys or questionnaires with Likert scale responses.

- **Progress Tracking:** This metric involves monitoring and recording each student's progress throughout the experiment. It can include data on completed modules, time spent on tasks, and the number of exercises attempted and mastered.

  Dataset: The dataset used for this experiment consists of English language curriculum materials typically taught in the 3^{rd} to 10^{th} grade.

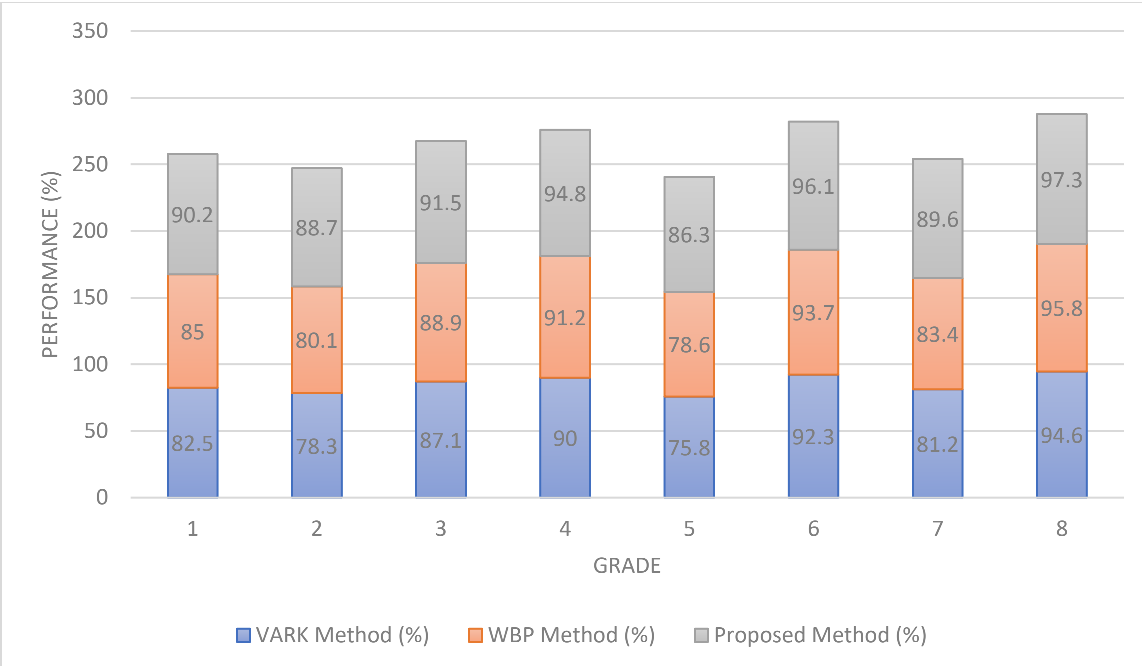

Figure 2: Academic Performance

The academic performance results demonstrate that the Proposed Method consistently outperformed both the VARK and WBP methods across all eight datasets. The improvement in academic performance, as measured by the percentage increase in post-test scores compared to pre-test scores, was notably higher for the Proposed Method. This suggests that the adaptive personalized e-learning platform, incorporating elements such as VARWK presentation, gamification, exercises difficulty scaffolding, and cognitive adaptation, effectively facilitated better learning outcomes for students.

The VARK and WBP methods also showed improvements in academic performance compared to the pre-test scores, but the gains were generally lower. This indicates that while traditional methods like VARK and WBP have their merits, the adaptability and personalized approach of the Proposed Method offer a clear advantage in enhancing students' learning effectiveness.

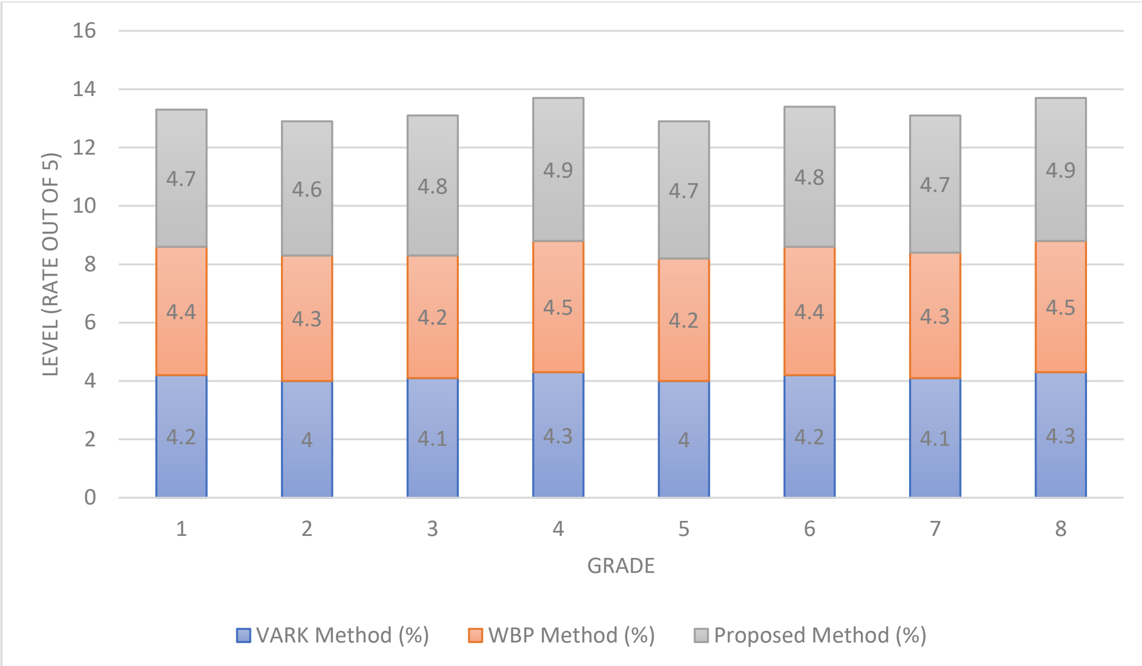

Figure 3: Satisfaction Level

The satisfaction level results indicate that the Proposed Method received the highest satisfaction ratings from students across all eight datasets. Students reported higher levels of satisfaction when using the Proposed Method, as reflected in the Likert scale ratings. This can be attributed to the engaging gamification elements, personalized content delivery, and adaptive feedback and guidance provided by the platform.

While both the VARK and WBP methods received favorable satisfaction ratings, they fell slightly behind the Proposed Method. This suggests that students appreciated the tailored learning experience and real-time adaptability offered by the Proposed Method, which contributed to higher overall satisfaction.

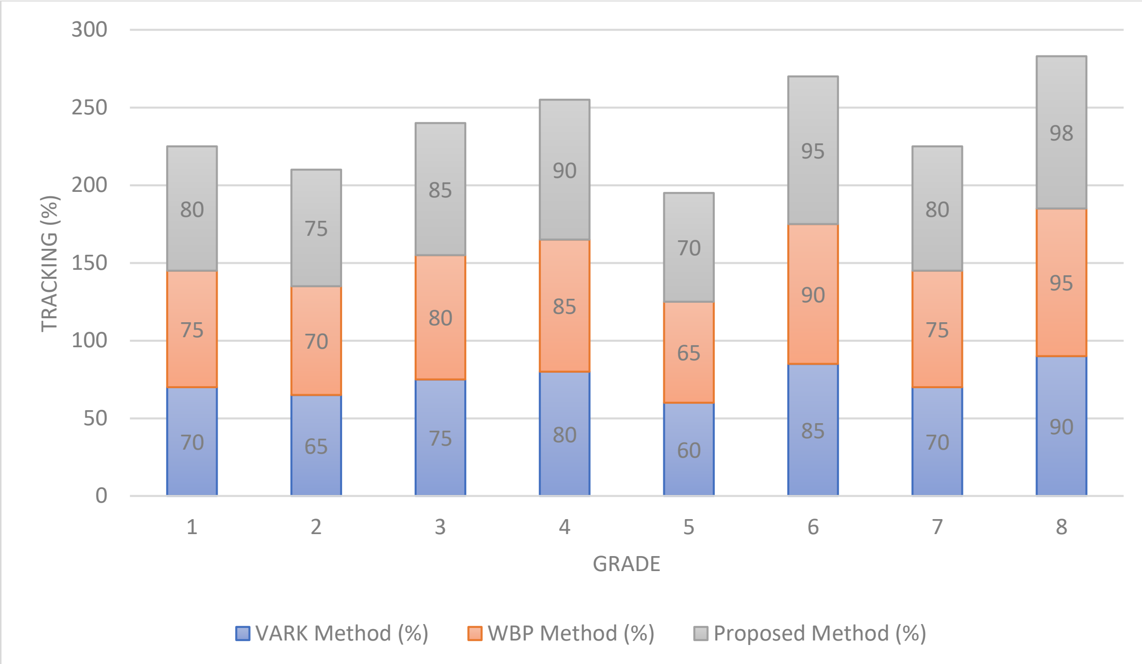

Figure 4: Progress Tracking

The progress tracking data, represented as completion percentages, show that the Proposed Method consistently had the highest completion rates for the learning materials in all eight datasets. This indicates that students using the Proposed Method progressed further through the course content compared to those using the VARK and WBP methods.

The adaptive nature of the Proposed Method, which adjusts content difficulty based on individual performance and preferences, likely contributed to this higher progress rate. Students might have felt more motivated to continue their learning journey due to the personalized approach, gamification elements, and timely feedback.

5. Conclusion

In an era where effective and engaging e-learning solutions are imperative, particularly for K-12 education, this study introduced an Adaptive Personalized E-Learning Platform. The platform combines VARWK presentation, gamification elements, exercises difficulty scaffolding, and cognitive adaptation techniques to cater to diverse learning styles and cognitive levels among students. Through a pilot experiment conducted on grade 3 English curriculum, we evaluated the platform effectiveness and user satisfaction. The results of the experiment demonstrated that the

Proposed Method consistently outperformed traditional methods, such as VARK and WBP. The academic performance of students using the Proposed Method showed significantly higher improvements compared to the other methods. This emphasizes the platform ability to adapt content, provide engaging learning experiences, and offer timely support, all contributing to enhanced learning outcomes.

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