# Personalized Hint Delivery in Multimedia Learning Environments Using Learning Styles: An Integrated Approach with Artificial Neural Networks and Weighted Sum Model

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***Abstract*— This paper introduces a novel multimedia learning environment designed to support holistic learning of web development. ANNs and the WSM model have been adopted to implement the framework of the VARK learning style model in order to dynamically provide personalized educational hints that assist learners to overcome difficulties and deepen their understanding, thus acquiring a higher level of knowledge in a more general and effective way. In our approach, hints are not an adjunct but a core feature of the learning process, dynamically tailored to each learner in their time of need. An ANN combined with a WSM collaborates to achieve optimal delivery of these hints, ensuring they are timely and context-aware according to the learning styles of individual students defined by the VARK model. Students receive the best possible guidance to make learning much more effective. A structured questionnaire-based evaluation followed by statistical hypothesis testing showed promising results for the efficacy of this multimedia learning environment.**

***Keywords—advice; hint; help; assistance; e-learning; multimedia learning; VARK; visual; auditory; reading; kinesthetic; learning style; ANN; WSM***

## I. Introduction

In the digital times, multimedia learning environments have become part of our learning systems; thus, students are provided with dynamic platforms in which audio, visuals, and interactivity come together to provide a more effective educational experience [1, 2]. These environments use massive amounts of media for the simulation of real-life situations while presenting complex information in a manner that is impossible to attain within the confines of a classroom. The use of diverse media enables diversified learning activities and adjusts to the preferences of learners in a rich, engaging, and flexible learning atmosphere.

However, personalized hints in such multimedia learning environments have been seen to be very critical in providing the best learning outcomes for students [3]. Delivery of hints in this way can address the needs of each learner, providing appropriate support that matches the pacing and style of the learner. To a learner working through complex educational material, personalized hints act as just-in-time guidance, reducing cognitive load and enhancing understanding through the scaffolding of the content with personalized, contextually relevant support.

Delivery of these personalized hints marks a milestone in educational technology in deployment of techniques of artificial intelligence (AI) [4]. Several AI techniques have already been put into practice: machine learning algorithms, natural language processing, predictive analytics, to generate hints adaptively responding to the learner's need. Among the most effective methods are the Artificial Neural Networks (ANNs) coupled with the Weighted Sum Model. This combination leverages the adaptivity of learning within ANNs and the simplicity of decision-making within the WSM to yield an overall effective framework of offering precise and contextually appropriate hints.

ANNs are modelled after biological neural networks used in animal brains, consisting of nodes that interact with one another to function like a neuron [5]. These networks learn from complicated data input and can make decisions or predictions based on such knowledge about the patterns learned. In a multimedia learning environment, ANNs use data from different learner interactions and performances to develop insights into the most effective strategies of presenting hints to learners.

It was also determined that ANNs have become popular through educational technology systems, and the literature reviewed identified this fact [6-16]. For instance, research [6-8, 15] was performed in order to identify relationships between students' learning patterns and educational content, so that the learning process could be more personalized. Studies presented in [9, 10, 16] describe how tutoring systems can be tailored to individual preferences and needs, once again through the use of ANNs.

Another great application, reported in [11] deploys ANNs in building a recommendation engine to provide learners with the most appropriate learning activity and resources at every point of their learning journey. Other studies [12,13] have used ANNs to the extent of designing adaptive learning pathways, that is, which would tailor the kind and order of the learning activities to the student's whims and capabilities being considered.

Besides, [6, 14] have also stressed that analysis of learners' emotional responses is an important application of ANNs within an educational system. This emotion analysis will help the system to elicit and respond to learners' emotional states, thus increasing effectiveness. These studies, therefore, go to show the versatility and influence of ANNs toward making environments of learning be more responsive and learner-centered platforms.

The paper presents development and deployment of a multimedia learning environment tailored to the teaching of web development that includes such key technologies as JavaScript, AJAX, Python, jQuery and a number of graphic design applications. A major novelty of this environment is the integration of ANN and WSM within the VARK model of learning styles to support a flexible and responsive educational experience. This system will be aimed at providing optimal hints to learners in tackling the complex topic and practical problems usually associated with web development. The information in a hint addresses two dimensions: first, it needs to offer the learner support at the right time according to the situation, and second, it needs to optimize the learning process according to the learning style of every student. Utilizing ANN in tandem with WSM, the system decides and picks the type of hints that are optimal for each learner, thereby maximizing educational effectiveness and satisfaction of the learner. Different types of hints are made available in the form of visual, audio, full text or interactive simulations, which ensure that every student's learning preference will be well catered to. In order to establish the effectiveness of the proposed innovative learning environment, we have carried out an evaluation based on questionnaires using the tools of statistical hypothesis testing. This was done to ascertain the levels of engagement of users, and the relevance of the hints that were being offered, as well as the overall acceptance of the intelligent framework in a multimedia learning environment. The results of the test present very convincing evidence of a high level of acceptance by the learners and the very successful introduction of adapted educational technologies in the teaching of complex web development skills.

## II. APPLYING THE VARK MODEL IN PERSONALIZED HINT DELIVERY

There are a number of models in educational psychology that describe and classify the manner in which individuals would rather learn. Among them, the Myers-Briggs Type Indicator Learning Style Model, Kolb's Experiential Learning Styles, and the Fleming VARK model significantly help in approaching learning improvement by personalized instructional methods from a number of different points of view [17, 18]. The VARK model [19], which recognizes the four learning preferences as Visual, Auditory, Reading/Writing, and Kinesthetic, is very well adapted to the digital era; within it, multimedia learning environments are present in huge quantities. Indeed, this model's classification system is very highly related to the types of digital content and gives a lot of compelling reason to implement educational technology interventions.

The VARK model clearly explains learning preferences: Visual learners are prone to taking in information more easily by looking at diagrams, charts, or illustrations. Auditory learners prefer speaking to giving spoken instructions or explanations. Reading/Writing learners do best with information presented in text and detailed written instructions. Kinesthetic learners do best when involved physically or through tactile learning experiences. When these preferences are mapped to specific delivery models, it will greatly enhance learner engagement and comprehension.

In multimedia learning environments, personalized hint systems may be implemented based on the use of the VARK model, where hints are personal and adaptive to the learning style of the individual and to the context and material difficulty level. For example:

- For Visual Learners: Hints could come in the form of pop-up diagrams showing relevant processes, animated steps to solve a problem, or visual comparisons that make clear complex ideas.
- For Auditory Learners: Audio files offer step-by-step instructions, give explanatory notes, or pose context-specific questions that learners can consider and provide an oral response to.
- For Reading/Writing Learners: Detailed textual cues that provide definitions, thorough explanations, and even ask the learner to write a brief summary or list of bullet points can enhance learning and make the learning 'stick'.
- For Kinesthetic Learners: The hint system could include interactive simulations or digital labs, in which learners could manipulate variables, coupled with the hints to indicate physical actions to take if the platform supports that level of interaction.

That is, this customized approach ensures that the hints are not only content-specific but are also delivered in a way that is perfectly in line with how the learner naturally processes information. Applying the VARK model in designing hint delivery systems, new educational technologies, such as Artificial Neural Networks and the Weighted Sum Model, can be optimally set. Not only can these technologies adapt to the interactions of the learner to deliver support on a personal basis, but they also improve the learning process immensely.

Exploiting the potential, the VARK model's input is sophisticatedly individualized educational content in multimedia environments in which technology and pedagogy are integrated into the best learning environments. This integration not only yields better educational results but also ensures a richer, more engaging learning experience that is truly tailored to the numerous and varying needs of learners.

## III. Hints Delivery Framework Using ANN and WSM

Integration of Artificial Neural Networks (ANN) with the Weighted Sum Model (WSM) constitutes one of the centerpieces of our framework toward implementing personalized hints delivery in a multimedia learning environment. This combination allows the power of the ANN for capability in adaptation and learning from complex datasets and the robustness of WSM as an effective tool for Multi-Criteria Decision Analysis (MCDA). The systems together enable one to appropriately work out the dynamic adjustment of the educational content, paving the way for optimal tailoring of the hints toward enhanced learning.

This integrated approach can make the hint delivering system very dynamic and strong at the same time. Carefully constructed hints provided are explicitly embedded within the multimedia learning environment to best support the specific domain of the content being taught for both relevance and contextuality. The effectiveness of the extent to which a hint actually works becomes extraordinarily high when it is designed and provided to suit the preference of the learner's information processing style - according to the VARK model.

For our model, the VARK model classification (V for Visual, A for Auditory, R for Reading/Writing, and K for Kinesthetic) is input to the ANN. Each type of learning style has its specific weights associated with it to signify how much a learner would prefer that particular type of hint. Thus, this is a personalized and sensitive way of hinting because even when the learner has high weights for one style, the learner can still have a certain level of liking for the hints for the other learning styles too.

The operational mechanism of the ANN is further improved by the inclusion of WSM (Fig. 1). We assign weights for the different types of hints that correspond to every learning style and calculate the output by using the activation function of WSM. The result is a mapped output that correctly directs the proportional summation of hint types to be provided to every learner. We illustrate the process through which the outputs are calculated below:

$$Z_1=\Phi(Y_V W_{1V} + Y_R W_{1R} + Y_K W_{1K})$$

$$Z_2=\Phi(Y_A W_{2A} + Y_R W_{1R} + Y_K W_{2K})$$

$$Z_3=\Phi(Y_V W_{3V} + Y_A W_{3A} + Y_R W_{3R})$$

$$Z_4=\Phi(Y_V W_{4V} + Y_R W_{4R} + Y_K W_{4K})$$

$$Z_5=\Phi(Y_V W_{5V} + Y_R W_{5R} + Y_K W_{5K})$$

These equations explain how each weight of the hint type, represented by W, combines with the intensity of the preference, represented by Y, for every learning style in order to yield a tailored hint distribution for every learner.

The ten educationists used for the mix of university professors and teachers from primary and secondary schools were all carefully designed with the weights and types of hints embedded in the ANN. All had over 10 years of working in the educational field and held PhDs, giving some useful inputs as to how best to evolve the parameters of the ANN for educational use.

Hence, the ANN output is, at the end of it all, well-tuned into a percentage of types of hints assigned to each learner, directly reflecting his or her own preference for learning style. A tailored approach guarantees every student will receive the best effective mix of hints that will dramatically boost personalization and effectiveness of the learning experience.

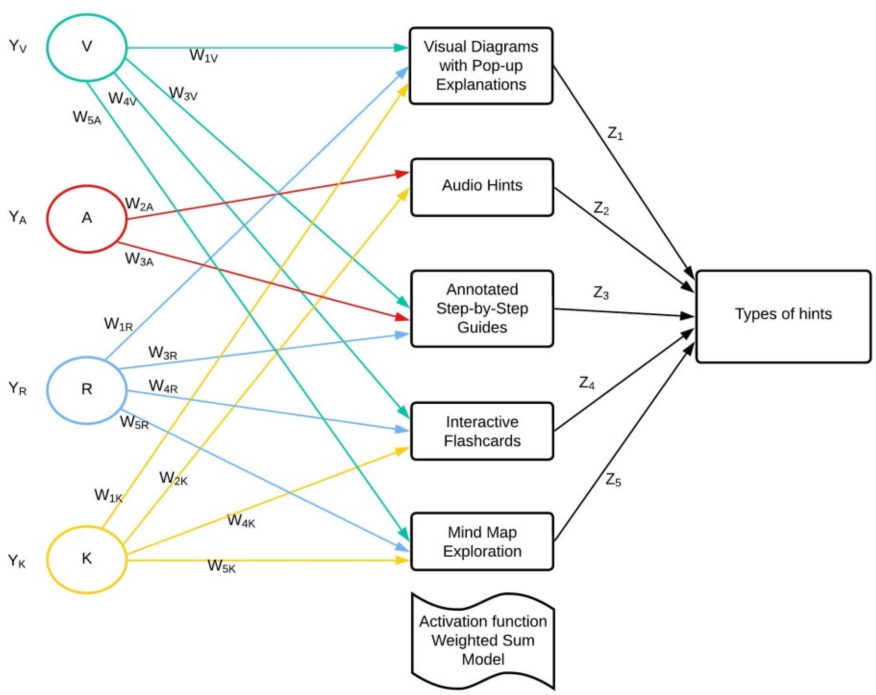

Fig. 1. Architecrure of the ANN.

To illustrate the functionality of the ANN combined with the WSM in our personalized hints delivery system, let's analyze the case of a hypothetical student named Filippos. Based on the system's log files, Filippos's learning preferences are distributed as follows:

- Visual (V): 70%
- Auditory (A): 30%
- Reading/Writing (R): 0%
- Kinesthetic (K): 0%

To determine how these preferences influence the delivery of personalized hints, we must first assign specific weights to each type of hint associated with these learning styles. The corresponding weights receive the following values: $W_{1V}$=0.7, $W_{3V}$=0.1, $W_{4V}$=0.1, $W_{5V}$=0.1, $W_{2A}$=0.3, $W_{3A}$=0.7.

These weights are the input to the activation function, which has the following outputs:

- $Z_1 = 0.7\times0.5 = 0.35$
- $Z_2 = 0.3\times0.3 = 0.09$
- $Z_3 = 0.7\times0.1 + 0.3\times0.7 = 0.28$
- $Z_4 = 0.7\times0.1 = 0.07$
- $Z_5 = 0.7\times0.1 = 0.07$

According to the weighted output of the calculated preferences and assigned weights, the predominant will be the visual diagrams with pop-ups. According to the weighted output, the best proportion for hint delivery of Filippos is the visual inputs. Thus, Filippos will benefit maximally from the visual hints, which are perfectly well-suited to the main mode of information processing of this respondent. In addition, Filippos will receive a very large amount of annotated step-by-step guides. Even though this learning style is not overwhelmingly visual for him, it still provides a significant contribution to his learning process. He will be able to perceive and remember the material more thoroughly. For Filippos, therefore, these personalized hints with graphic diagrams and annotated guides fit his personal learning profile. In this respect, he will best understand and learn from educational material through providing him with hints in such formats, he will properly engage with educational material, and his learning outcomes are optimized.

## IV. Evaluation Results

In this paper, we assess our multimedia learning environment with the Lynch & Ghergulescu framework [20] purposely designed to evaluate adaptive and intelligent tutoring systems. The evaluation takes place according to four critical dimensions: learning and training, system, user experience, and affective dimension. The "learning and training" dimension examines the quality of the educational process effectiveness and efficiency and of the process of knowledge acquisition by the students. The "system" dimension rates the effectiveness of the software or application in use while relying on algorithmic techniques to lend assistance to the learners in knowledge acquisition. The "user experience" dimension evaluates the attitude of the students towards the use of the system, while the "affective" dimension evaluates the students' affect state induced during the interaction with the software.

In this evaluation the test group was made up by 60 graduate students from the Department of Informatics and Computer Engineering of a public university. All participants were test students for a postgraduate program on Information Technology and Applications and, respectively, attended a course on web development. The testing took place during 13 weeks and after this period the students were asked to fill in two questionnaires developed around the Lynch-Ghergulescu framework. The questionnaires had twelve questions, rated from 1-10, where 1 was the lowest and 10 the maximum mark, as illustrated in Table I.

TABLE I. QUESTIONNAIRE

| Dimension (D) | No | Question |
|---|---|---|
| Learning and Training System (D1) | 1 | Rate your learning outcome improvement. |
| | 2 | How efficient is the use of time? |
| | 3 | Rate the relevance of the type of delivered hints to your learning style. |
| | 4 | Rate the helpfulness of the delivered hints. |
| User experience (D2) | 5 | Rate your satisfaction. |
| | 6 | Rate your overall experience. |
| | 7 | Rate the easiness of use of the environment. |
| | 8 | Rate the familiarity of the environment. |
| | 9 | Rate the quality of the environment. |
| | 10 | Rate the usefulness of the environment. |
| Affective dimension (D3) | 11 | Rate your engagement with the environment. |
| | 12 | How motivating is your learning experience? |

The responses from the students to the questions listed in Table I have been compiled according to the framework's dimensions and are displayed in Fig. 2.

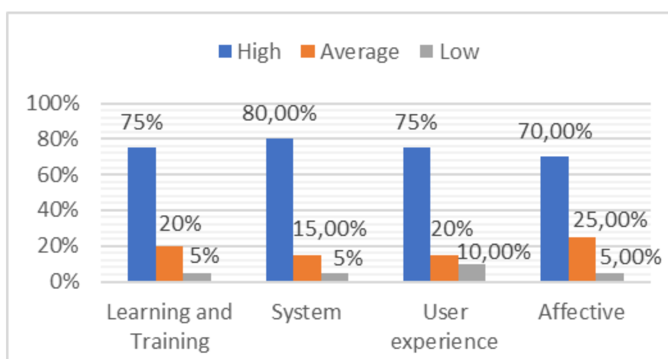


Fig. 2. Results from questionnaire.

Upon analyzing the evaluation results, it becomes apparent that the multimedia learning environment presented is highly effective in enhancing learning outcomes. This efficacy is largely due to its ability to successfully deliver personalized hints to students. This is achieved through the integration of an intelligent mechanism that combines ANN and WSM, further refined by incorporating the VARK model of learning styles. The learning strategy, embedded within a digital gaming framework, effectively addresses multiple dimensions of the evaluation framework, which can:

- Significantly improve students' learning outcomes by providing targeted educational support (D1).
- Enhance the efficiency of hint delivery, utilizing sophisticated algorithmic techniques that ensure timely and relevant assistance (D2).
- Create a user-friendly and enjoyable learning experience that encourages continued engagement (D3).
- Maintain high levels of engagement and motivation among learners, making the educational process both stimulating and rewarding (D4).

To obtain more comprehensive insights and to assess the effectiveness of the algorithmic technique incorporated in the multimedia learning environment, a t-test was also conducted. This statistical test compared the presented learning environment to a conventional version, which featured the same user interface and domain content but lacked the sophisticated hint delivery mechanism utilizing ANN and WSM. Instead, hints in the conventional version were distributed randomly. The innovative learning environment was utilized by 60 students (Group A), as previously noted, while the conventional version was engaged by a separate cohort of 60 students (Group B). Both groups were matched to ensure homogeneity in demographic and academic characteristics, allowing for a controlled comparison. The focus of this evaluation primarily revolved around the effectiveness of the system's integrated technological enhancements. Accordingly, the t-test was applied specifically to the responses to Question 3, aiming to statistically ascertain the impact of the advanced hinting techniques on learning efficacy. The outcomes of this analysis are detailed in Table II.

TABLE II. T-TEST RESULTS.

| Metric | **Question 3** | |
|---|---|---|
| | Group A | Group B |
| Mean | 4,066667 | 3,25 |
| Variance | 0,978531 | 0,800847 |
| Observations | 60 | 60 |
| Pooled Variance | 0,889689 | |
| Hypothesized Mean Difference | 0 | |
| df | 118 | |
| t Stat | 4,74227 | |
| P(T<=t) one-tail | 2,98E-06 | |
| t Critical one-tail | 1,65787 | |
| P(T<=t) two-tail | 5,97E-06 | |
| t Critical two-tail | 1,980272 | |

Reviewing the results from Table 2, we observe a statistically significant difference in the mean scores of the two groups for Question 3. This obviously indicates that the multimedia learning environment integrated with advanced delivery techniques makes a remarkable difference over the traditional environment. The superiority of the developed system can be adequately validated through the means of advanced techniques implemented for delivering adequate and personalized hints. It could easily be expected since the learning environment reviewed in this paper houses an intelligent mechanism. This system houses Artificial Neural Networks (ANN), the Weighted Sum Model (WSM), along with a learning style model to make the delivery of hints as required maximized to facilitate the learning process. This fusion of technologies bestows a sturdy framework through which the process of hint delivery is significantly optimized and therefore assures the advanced competencies of the system developed to enhance educational results.

## V. CONCLUSIONS

There is increasing evidence that multimedia learning environments could be a highly motivating and effective educational tool that has enabled learners to achieve their goals. This paper reported an advanced multimedia learning environment designed to optimize learning outcomes through a customized delivery method of hints. Through an intelligent mechanism that provides for learner learning styles, and using ANN and WSM, this system is able to determine and distribute the most effective hint types according to individual learning styles.

The testing of this learning environment also renders a positive result pertaining to the effectiveness of enhancing student learning with personalized instructional support. The integration of advanced computational models with pedagogical strategies forms an important advancement in the design of educational technology that offers more adaptiveness and responsiveness in the learning process.

Our future work is oriented towards extending the adaptability and reach of the learning environment. We plan to add more learning styles to study their effect on the system's effectiveness and expand the adaptability of the hint delivery mechanism. Also, to be done is a more extensive evaluation of the system with the hope of increasing the validity of the benefits of the intelligent mechanism in different varied educational scenarios and over a bigger student body.

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