

An ANN-WSM Hybrid Framework for Sustainable Personalized Learning in Smart Education

Christos Troussas, Akrivi Krouska, Phivos Mylonas, Cleo Sgouropoulou, and Ioannis Voyiatzis

Department of Informatics and Computer Engineering, University of West Attica
Egaleo 12243, Greece

{ctrouss, akrouska, mylonasf, csgouro, voyageri}@uniwa.gr

Abstract. Personalized learning in modern education helps create learning experiences based on learners' individual preferences. This paper presents an adaptive learning system integrated with ANNs and WSM that recommends particular learning activities to students based on their cognitive styles. The system classifies learners according to the Gregorc Mind Styles Model and, through the ANN, provides probabilities of predefined learning activities. Static expert-assigned weights in WSM finalize the recommendations with adherence to pedagogical best practices while harnessing AI-driven personalization. This implies that a fundamental way this system contributes to sustainable education is that it dynamically optimizes the recommendations on which learning activities are proposed to boost engagement, retention of knowledge, and instructional efficiency. In this way, it undertakes enabled, resource-efficient learning by correspondence of learning activities that require little, if any, mismatch with instructional materials and minimal manual intervention. The weights of WSM, provided by experts, are static constants which contribute to higher decision-making stability, simplicity of resource consumption on computations, with the strong achievement on recommendations. In the pursuit of assessing our approach, we embedded this system in an educational software platform for C++. A study involving 70 undergraduate students found significant improvements in engagement, retention, and performance. The results validated ANNs-implemented adaptive learning using the WSM-based ranking, laying the foundation to improve personal education both in terms of a well-organized and sustainable manner. The research captures the potential of learning systems driven by AI as becoming a transformative mode to deliver efficient, broad-scale, and bespoke education.

Keywords: Adaptive Learning Systems, Artificial Neural Networks in Education, Personalized Learning, Recommendations, Sustainable Education, Programming Education.

1. Introduction

Educational software has changed the way modern learners engage by rendering dynamic and scalable learning experiences [1]. Such technologies have incorporated methods through which learners can engage with educational content in other dynamic, interactive ways. Broadly speaking, this means the incorporation of multimedia elements, simulations, and adaptive assessment tools into the learning process, which is indeed a

better one over static textbooks and a one-size-fits-all type of instruction [2]. Through the interactions of educational software, many students can enjoy personalized learning as they progress with their own pace, revisit complex concepts when they deem fit, and access material that meets their specific needs [3]. Besides, by enabling greater access to knowledge, these systems also really help in overcoming social-economic or geographical or logistical yet relevant constraints in order to ensure that quality education is being accessed and rendered at a great population scale.

The most transformative moment for modern educational software is set by the integration of Artificial Intelligence (AI) that champions unprecedented personalization. Driven by AI, such systems exploit quite complex algorithms for analyzing students' interaction behavior so as to predict their learning preferences so that the instructional content could be dynamically adjusted in real-time [4]. Machine learning techniques can identify strengths and areas for improvement in an individual learner and deliver an adaptive and individualized experience. These intelligent systems cause levels of difficulty to be increased or decreased, they recommend further resources, and provide context-sensitive feedback, keeping the students interested and motivated during their learning experience [5]. Teachers will be able to transition from a static instructional approach to a data-driven and student-centered approach, supported by AI-driven insights ensuring the efficient and effective learning process.

The extent to which personalized learning systems are able to take into consideration learning styles is critical in determining their success, and these learning styles dictate how students perceive, process, and retain information [6]. In traditional forms of instruction, one common tendency is to take a one-size-fits-all approach underestimating the cognitive differences amongst the learners. Such underestimations equate to inefficiencies of knowledge acquisition with poorer engagement and retention rates. The integration of various learning styles in adaptive educational software allows for the differentiation of instructional delivery according to individual cognitive preferences [7]. In this sense, students engage in learning tasks that are compatible with their preferred modes of processing information, which would improve comprehension and retention. Thus, cognitive-based personalization strategies should be known and implemented in educational software for maximum student success.

Within the growth of AI techniques, in particular artificial neural networks (ANNs), many ideas thereby revolutionized adaptive learning systems [8], [9]. Using large sets of data analyzed through ANNs, complex student-type behavior patterns are easily identified, thereby giving recommendations for tailored learning. In comparison with rule-based systems that rely on existing heuristics, ANNs are robustness when learning from student interactions, updating their recommendations in a way that increasingly conforms to the changing needs of the learning. Other AI-driven approaches, such as reinforcement learning and natural language processing, also contribute to the development of intelligent, scalable, and very responsive educational solutions. These technologies add value to real-time adaptability, ensuring that learning experience remains dynamic, effective, and personalized.

In this paper, we propose an ANN-based adaptive learning model integrated with the Gregorc Mind Styles Model in order to optimize personalized education. It classifies students based on their cognitive types and predicts the most effective learning activities for them, which contributes to achieving an efficient and sustainable learning process. In con-

trast to traditional fixed-rule-based personalization methods, the proposed model dynamically adjusts the recommendations while students interact with the system, thus leading to more accurate and data-driven learning pathways. This is further improving engagement, increasing retention rates, and creating learning environments catered toward the unique needs of individual students. The experimental evaluation indicates that this model integrates the best of AI neural networks with cognitive science learning personalization for the benefit of promoting learner-centered learning.

2. Related Work

The integration of personalized educational software has become a salient aspect of contemporary learning environments, in which the instructional content is tailored to fit the individual student needs. The aim is to provide engagement and learning outcome improvements through customized learning experiences built upon data-driven insights. A few approaches to personalization exist, from rule-based adaptive learning systems, which use predefined sets of instructional rules, to machine learning-based models, which dynamically adapt to students' behaviors and learning progress ([10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22]). Such intelligent systems rely on multiple data sources to steer personalized learning pathways: prior academic performance, learning preferences, and real-time interaction history. The system adjusts for each student and provides recommendations aligned with their respective strengths and weaknesses; hence, deeper comprehension and retention become viable.

The one area where adaptive learning has made significant strides is the adoption of learning style models in educational software. Models, such as VARK (Visual, Auditory, Reading/Writing, Kinesthetic) [23] and Felder–Silverman Learning Style Model [24], develop theoretical bases to assign students to categories reflecting how they prefer to take in information. Such models have been dominating in most educational settings for overcoming engagement within an instructional methodology by matching it with their cognitive preferences [24], [25]. However, many of these models use static classifications, which assume that a student has a fixed learning style, and these will not change over time. Hence, the drawback is that reduced adaptability is restrained because they do not dynamically autoregulate based on students' constantly evolving learning behaviors and interactions with materials.

The application of artificial neural networks in educational software has potentiated dangerously adaptive learning [26]. ANNs provide an advanced computational means by ransacking wooden-sized volumes of student data, pinpointing the pattern, and forecasting the most effective learning activity possible. Whereas rule-based ones need to be strictly programmed to explicitly define instructional paths, ANNs furnish an instructor with data. These studies have shown improvement from ANN-driven adaptive systems that lead progressively to any learning, involvement of students, memory retention, and general efficiency [27], [28], [29], [30], [31], [32]. Using ANNs has allowed for a very granular and personalized approach where hidden correlations connect student performance, learning pace, and instructional preferences built on the streaming values. The infusion of deep learning technologies also packs these models tighter against the intricate gymnastics of student behavior. However, rather than merging both orientations into a unified model,

studies on intelligent learning still concentrate more on learning style adaptation through fixed rules or ANN-based recommendation systems.

In contrast to earlier hybrid approaches that combined machine-learning algorithms with multi-criteria decision-making techniques, the proposed framework introduces a cognitively grounded layer through the Gregorc Mind Styles Model (GMSM) [33]. Prior ANN-MCDA (Artificial Neural Networks-Multi-Criteria Decision Analysis) models typically relied on behavioral or performance metrics alone, whereas our method explicitly incorporates a cognitive-style classification that governs how learning activities are selected and interpreted by the ANN. The Weighted Sum Model (WSM) then serves not merely as a ranking mechanism but as a pedagogical filter that embeds expert knowledge to preserve instructional soundness. This tri-layered integration – cognitive profiling → neural prediction → weighted pedagogical optimization – constitutes a distinctive advance over prior systems by aligning algorithmic adaptivity with sustainable educational principles, minimizing redundant learning effort, and promoting resource-efficient personalization. Hence, the ANN-WSM-GMSM combination bridges psychological modeling with AI-driven adaptivity in a way not addressed by previous hybrid frameworks.

This paper strives to close this gap by implementing the integration of the Gregorc Mind Styles Model within the framework of an ANN-driven adaptive learning system. In difference from earlier models assigning fixed learning styles, our method will permit the ANNs to propose and recycle learning activity recommendations in light of real-time student engagement and their achievement in learning. With its adjustment to the changes of one's cognitive styles, our model guarantees that materials for study remain vividly relevant even after a long time has passed. The incorporation of multi-criteria decision analysis, WSM specifically in our model, further amplifies the accuracy in recommending which learning activities one should pursue.

To the best of our knowledge, no prior adaptive learning framework has explicitly integrated the Gregorc Mind Styles Model within an ANN-WSM hybrid architecture. Existing hybrid systems combining artificial neural networks and multi-criteria decision-making approaches have focused primarily on behavioral or performance-based adaptation. In contrast, the proposed model introduces a cognitively grounded mechanism that links neural prediction with pedagogical weighting, constituting a novel, data-driven personalization approach oriented toward sustainable education.

3. Gregorc Mind Styles Model incorporation

Building upon this identified gap, the present study operationalizes the Gregorc Mind Styles Model within an ANN-WSM adaptive architecture to demonstrate its practical impact on personalized and sustainable learning.

The Gregorc Mind Styles Model [33] is a cognitive framework that identifies the different ways by which a learner perceives and organizes information. In that model, one comes to understand the individuality of the learners, which is quite significant in the effective design of adaptive educational systems. In contrast to conventional models of learning styles that regard sensory modalities, Gregorc's approach acknowledges the diverse ways in which the individual learners approach and process knowledge. Analysis of such cognitive preferences would help personalize the learning experience in a way that is natural to and harmonious with the students' context of assimilating information.

Gregorc, then, recognized four different cognitive styles that portray the manner through which individuals tackle learning tasks. Concrete Sequential learners work best and on well-organized, orderly set formats and instructions. Those learners would seem to perform best when a task was clearly outlined or categorized in orderly steps. Because he or she depends on a predictable sequence for teaching and learning styles, an individual best performs under these stipulated methods because of a more structured version of the other Concrete Random category or kind of learner. The Concrete Random learner, however, is more tantalized with experiential modes for learning, wherein negotiations for new ideas could be bid during experiments. Those learners would like to discover new ideas for themselves through experimentation; thus, they are apt at creative and innovative settings as well as in the solution of a problem. He or she believes that rigid formality from teaching or learning content leaves little space to roam free and become explorative in learning tasks.

Abstract Sequential learners associate themselves with logical theoretical constructs and prefer analyzing concepts in somewhat orderly fashion. Their performance in acquiring information would be enhanced through reading, structured lecture presentations, or detailed research. Effective evaluation and integration of information is their strength, hence learning in analytical environments is easy for them. On the other hand, Abstract Random learners are strong in social and relational environments. Collaborative learning environments and group discussions allow those learners to share ideas with their companions. Such students connect emotionally with a particular piece of information to remember it and are taught most likely in a person-oriented way where he or she is allowed to roam free in questions and answers.

The main addition of using the model in an AI-based learning paradigm is its particular advantage for continuous improvement—perhaps, which might not be possible through most traditional learning style models with set preferences or dimensions which don't just take into account the shifting cognitive preferences for the learner. This allows for the system to use an ANN in order to analyze behavior patterns, learning outcomes, and engagement metrics based on these decisions. The result is an iterative loop of improvement, which plays into the potential for further personalized recommendations. The Gregorc Mind Styles Model in adaptive learning not only helps with sorting learners but structurally informs the way in which learning activities should be planned. The AI-driven predictions allow instructional content to be updated continually so that learners would be engaged in the material according to the cognitive style with which they can understand most. Hence the personalization includes in its parameters life authorizing learning for optimizing resources and thus growth of general learning efficacy. The Gregorc Mind Styles Model is a cognition-based model helping to classify individuals based on preferred ways of perceiving and ordering information. It incorporates the information of how learners actually process knowledge and interact with learning materials, making it highly relevant for any adaptive learning systems.

Gregorc's model divides learners into four different cognitive styles:

- Concrete Sequential (CS) - These learners prefer structured, step-by-step instruction and are good at organized tasks, listening to instructions, and hands-on activities.
- Concrete Random (CR) - They learn best by trial-and-error and prefer exploring new ideas by working hands-on or creatively solving problems.

- Abstract Sequential (AS) - These learners value logical theories and structured conceptual frameworks and are good at reading, researching, and analyzing data.
- Abstract Random (AR) - These learners prefer discussions, collaborative learning, and brainstorming activities while putting a lot of emphasis on group interactions and emotional attachments to the learning material.

4. ANN and WSM for Recommending Learning Activities

The recommender system for learning activities developed in this research employs an ANN along with MCDA, specifically the WSM [34]. This paradigm affords the integration of structured decision-making and adaptive learning to ensure giving the most suitable recommendations in case deciding the learning activities is concerned. The model is bound by the Gregorc Mind Styles Model and provides the basis for classifying learners to feed the ANN that will be used for producing personalized recommendations. Cognitive styles influence in each student the type and pattern of learning activities that suit the person best. For their integration within the ANN, various weights are assigned for learning styles according to that learning activity's probability of engagement and effectiveness among the many instructional recommendations that could be offered. This helps in providing dynamic alignment between the learning content and student needs, from static candidacies to a model that is adaptive and continually evolving. A Concrete Sequential learner would rather have structured, step-by-step instructional tasks such as solving problems and learning activities that ask them to go through a certain procedure. But this would usually mean they are engaged with the specific type of learning activity, albeit somewhat proportioned, where some would take priority over others. Also, an Abstract Random learner would be more or less inclined to learn through brainstorming, collaborative learning, or learning through discussions but again with some variance in intensity. The ANN will use WSM to ascertain preferences given the weights relevant to each learning activity and map said computed values to the most recommended learning tasks, as shown in Fig. 1.

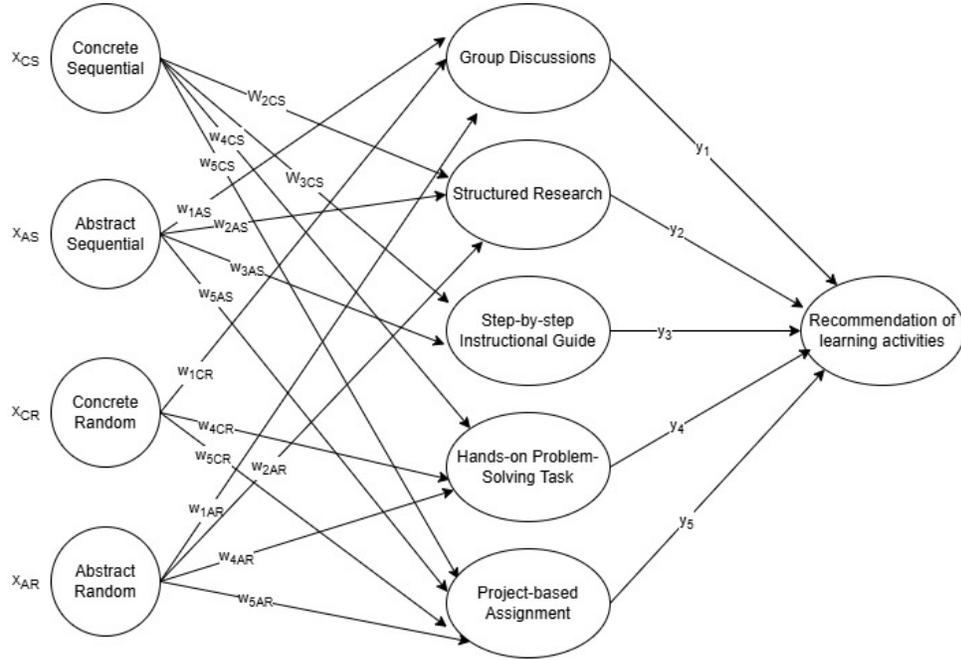


Fig. . Architecture of ANN and WSM.
 The output of the presented system, based on WSM, will be as follows:

$$y_1 = \Phi(x_{AS}w_{1AS} + x_{CR}w_{1CR} + x_{AR}w_{1AR})$$

$$y_2 = \Phi(x_{CS}w_{2CS} + x_{AS}w_{2AS} + x_{AR}w_{2AR})$$

$$y_3 = \Phi(x_{CS}w_{3CS} + x_{AS}w_{3AS})$$

$$y_4 = \Phi(x_{CS}w_{4CS} + x_{CR}w_{4CR} + x_{AR}w_{4AR})$$

$$y_5 = \Phi(x_{CS}w_{5CS} + x_{AS}w_{5AS} + x_{CR}w_{5CR} + x_{AR}w_{5AR})$$

In order to ensure that the weighting system honestly reflects real-world educational needs, weight assignments of the ANN through a Delphi method were obtained from a panel of 14 experienced educators culled from university professors from diverse academic disciplines. Each of these experts had at least 12 years of teaching experience, and to them, the panel assigned the value of their insights on how the different cognitive styles influence learning preferences. Harnessing expert-guided inputs from the panel has ensured that the model's recommendations are pedagogically sound and resonate with the realities of educational practices on the ground. The ANN does output a percentage distribution of learning activities for each learner, effectively showing the inclination of varied teaching strategies to be aligned to each person's cognitive style. This means that it offers flexibility for the Instructional Designer in arranging materials into a mix

that caters to the kind of learning experiences likely to fit their learning styles. Once it's done doing all this data passage, it suggests some learning activities. As an example, Maria's case shows how this recommendation process actually works. The system has checked Maria's learning style via the recognition of her previous learning behaviors and interactions in academic life: The findings were of 70% Abstract Random and 30% Abstract Sequential. Meaning that Maria would prefer collaborative learning, brainstorming, and discussion-based activities but would also benefit from structured research assignments and analytical exercises. The expert panel assigned the following weight values: $w_1 = 0.7$, $w_2 = 0.3$, $w_3 = 0.4$, $w_4 = 0.6$, $w_5 = 0.5$. With the use of these weights run through the WSM activation function, it becomes possible for the system to discern the most suitable learning activities for the students. In fact, according to these calculations, Maria will mostly be recommended for collaborative brainstorming and talking sessions, owing to her dominant Abstract Random learning style. The ANN constantly fine-tunes its recommendations as fresh data of interaction from students is collected. This continuous adaptive capability ensures an ever-advancing level of precision that adds more value into personalization and optimization of learning pathways as time goes on. By blending ANN and WSM, the system combines personalized instruction with a commitment to developing an efficient, engaging, and sustainable learning environment. Integration such as this limits the chances of mismatches in instructional materials, decreases cognitive overload, and guarantees that learners engage in activities well suited to their changing educational needs.

5. System Architecture and Implementation Details

The system employs a dataset comprising student interaction data, engagement with learning activities, and performance evaluations from a combination of diverse educational settings. Since the dataset contains students' answers, the time devoted to different activities, frequency concerning different instructional techniques, and self-reported preferences in agreement with Gregorc's cognitive styles, it is preprocessed to erase any inconsistencies and normalize values to reach reliability for the complete ANN training. Each student is assigned a learning Style AN in terms of associations with respect to thought processes. Such classification is used essentially as the input features for the ANN model. The ANN is a multi-layer perceptron, principally composed of an input, one hidden, and an output layer that produces recommendations for suitable learning activities to an individual learner. In terms of high performance, a justification is presented whereby a single hidden layer is taken as an assumption for the reason that if one is used, there will be efficiency in the computation such that one can model easily the relation between learning styles and the mode in which students preferred to get engaged along the process itself. The input layer receives the learning style classification; this is converted to numerical representations on which the network can act. Non-linear activation functions are used in the hidden layer to get complex relations between learning styles and engagement activities. This layer relays to the output organs a probability distribution of different activities, referring to the type of activity's efficacy and the likelihood that it will engage the particular student. The activation function used in the hidden layer is the ReLU (Rectified Linear Unit), defined as:

$$f(x) = \max(0, x)$$

For the output layer, a softmax activation function is applied to ensure that the recommended learning activities form a probability distribution:

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

Where $P(y_i)$ represents the probability of selecting learning activity i , and z_i is the corresponding output score.

An artificial neural network that receives labeled interactions from students is used to train the model; backpropagation with SGD is used to optimize the network weight values. The loss function minimizes the distance between predicted learning activity preferences and the actual engagement patterns that are observed in the historical data. A multitude of learning iterations is performed to continually refine the model's accuracy and ensure generalizability across varied student populations. Cross-validation methods are used to avoid overfitting and support the reliability of the model.

In addition to the ANN's prediction capabilities, the final recommendation process incorporates the Weighted Sum Model (WSM) to enhance decision-making. Unlike the ANN, which learns and refines student learning preferences based on historical data, the WSM operates using fixed expert-assigned weights to prioritize learning activities. As mentioned earlier, these weights were predefined by a panel of experienced educators. The assigned weights reflect pedagogical best practices and determine the importance of each learning activity type for students with different cognitive styles.

The WSM score for a learning activity S_i is calculated as:

$$S_i = \sum_{j=1}^n w_j x_{ij}$$

where S_i is the total score assigned to learning activity i , w_j represents the expert-defined weight assigned to criterion j , and x_{ij} is the score of learning activity with respect to criterion j . These values do not change dynamically but remain constant throughout the learning process to ensure consistency in decision-making.

From the standpoint of computation, the system is implemented with Python using TensorFlow and Keras for neural networks, with NumPy and Pandas for data preprocessing and analysis. Training of ANN occurs in a high-performance computing environment that utilizes GPUs (Graphics Processing Units) or TPUs (Tensor Processing Units) in order to accelerate matrix operations and optimize the efficiency of backpropagation. The model accommodates real-time inference for on-demand personalization of learning recommendations without introducing latency to a significant extent. This system is also scalable, intended for large-scale student datasets in online and blended educational settings. By virtue of combining ANN with WSM, the system dynamically adapts as new student records become available while constantly refining its recommendations to make learning personalized. However, WSM weights remain fixed as per predefined expert knowledge; hence, the final ranking of learning activities adheres to educationally accepted standards. By this hybrid approach, the predictive power of machine learning is combined with structured decision-making in such a way that the learner's experience remains reliable, efficient, and pedagogically sound.

6. A Sustainable Approach to Personalized Education

One of the main strengths of the proposed adaptive learning system based on artificial neural networks (ANN) is its input into ensuring that education is sustained. By sustainability in education, not just responsible resource use, but greatly adjustable long-term learning models which are favorable to various learners while maximizing educational efficiency should also be taken into account. The old one-size-fits-all instructional models are generally static, incapable of addressing individual learning needs. Such methods led to unnecessary investment in instructionally rendered time, motivating pupils to turn away from the ideal tasks and engaging in resource wastage. However, the AI-based personalized model of learning optimizes learning pathways so that students are involved with materials designed for concern effectiveness and were not wasteful of resources. The sustainability of this approach depends on less redundancy in education. With much frustration, many a learner is provided classroom material which is not commensurate with the way he/she thinks or learns best. Traditional paradigms often force students to revisit what they already know or labor through materials that do not suit their learning style. The proposed model, however, cuts these inefficiencies down via the immediate engagement of student-level data and the adaptation of recommendations in ongoing iterations. Learners are hence afforded inculcative interventions pitched with precision, which aids rapid acquisition with little intervention in revisiting past lessons. Further, education sustainability also applies to resources from technological and human intervention. The integration of ANN and WSM in the system makes possible the taking or culmination of activities in personalized learning, which would often require much of educator's attention. This means less burden on instructors and, thus, more time spent engaged in more meaningful pedagogical interactions such as activities to stimulate creative thinking as opposed to administrative ones like content assignment and tracking the performance of learners. Insights emanating from the recommendations of the system can help teachers in further adjusting their pedagogies in class, such that both AI-driven learning and human-led should act in concomitance with one another.

The system promotes sustainable e-learning from an environmental and digital resource perspective by means of minimizing unnecessary digital consumption. Many e-learning platforms unnecessarily build vast amounts of digital content, thereby making that content largely unused due to a lack of personalized targeting. This approach proposed will make sure that students get only those resources that are most relevant and beneficial, reducing excessive data storage and much of what otherwise would be applied to computation. This is also majorly contributing to reducing dropout rates since improved engagement and retention was a big problem throughout online education. A sustainable e-learning environment will keep the students motivated to go all the way through their learning journey with an applause retention and success rate at the end. Lastly, the capability of this approach to be scalable makes it highly sustainable for massive-tier educational implementation. Because the model is learning and unlearning from new student-specific interactions continuously, it gets more refined over time without requiring ongoing manual adjustments. This makes it suitable for large institutions in education, online learning services, and lifelong learning programs. With the boom of AI-centric education, sustainability has increasingly been turned into a major consideration, and such a model offers a pragmatic way to go about personalization, efficiency, and futuristic versatility.

7. Case studies

In order to address the fairness within the context of proposed ANN-WSM adaptive learning system application, we examine three cases of students who have distinct styles of learning. Each case shows in detail how the student's learning style feeds into the ANN, how WSM weights the learning activities, which ultimately results in personalized recommendations. These cases will give evidence for the system's integration into personalized learning based on cognitive preferences while continuously utilizing the already set five predefined learning activities.

7.1. Case 1: Maria – Abstract Random Learner

Maria is said to be 70% Abstract Random and 30% Abstract Sequential, so she performs best in collaborative and discussion-based learning environments while she also benefits from structured research. Her classification of learning style works as an input into the ANN, where numerical weights are given according to her distribution of preferences. Using the softmax activation function, the ANN evaluates the probability of various learning activities for Maria. The Weighted Sum Model (WSM) then fine-tunes these probabilities by assigning each of them empanelled weights by experts. The WSM function is computed as follows.

$$S_i = \sum_{j=1}^n w_j x_{ij}$$

where S_i represents the score for each learning activity, w_j represents the assigned weight, and x_{ij} is the engagement score.

Maria's final recommendations are on a heavy emphasis on collaborative discussion and project-based assignments. This boosts her engagement, whilst also helping her develop ways of processing and synthesizing all the information and ideas through structured inquiry.

7.2. Case 2: Alex – Concrete Sequential Learner

According to Alex's cognitive classification, he is 90% Concrete Sequential and 10% Concrete Random, preferring structured, procedural tasks, benefiting from clear, well-defined learning objectives. Accordingly, the input vector in ANN responds to these preferences, enhancing the debugging methodology involving step-by-step instructional guides and structured research. The ANN processes Alex's classification and provides the WSM with an initial probability vector regarding various learning activities. With regard to the pedagogical strategies defined by the experts, the WSM model subsequently assigns the weights. Given the weight assigned to the structured learning, these traditional methods are bound to be reinforced in by way of learning.

- High weights to step-by-step instructional guides and structured research
- Low weights to collaborative and exploratory learning activities

As a result, Alex's recommended learning activities focus on step-by-step guides and structured research, ensuring an effective and engaging experience that aligns with his learning tendencies while minimizing unstructured, discovery-based learning approaches.

7.3. Case 3: Sofia – Balanced Learner (Abstract Sequential & Concrete Random)

An abstract sequential and concrete random cognitive style assigned Sofia a 50% and 50% knowledge of mixing both logical and sequential learning and hands-on activities. This balanced profile creates a problem for adaptive learning systems because it needs to evenly distribute recommendations between theoretical and hands-on tasks. In putted with an ANN 50% toward structured research or hands-on problem-solving tasks, probability distribution appears the same. Hence, the model assigns weights to ensure diversification in terms of Sofia's strengths. Learners could pay more attention to logical learning and hands-on problems in a manner such that they would develop a good combination between analytical reasoning and creative exploration to maintain a good engagement context in the lesson given. This thus becomes an integrated strategy to guarantee that Sofia has an all-around experience-fitting outline unique to the cognitive style preferences. Table 1 illustrates the recommendations in learning activities for all the other students, supposedly showing the dynamic adaptation of the ANN and WSM concerning learning style preferences.

Table . Learning activities recommendation.

Learning Style Classification	Recommended Activities
Maria 70% Abstract Random, 30% Abstract Sequential	Group discussions, project-based assignment
Alex 90% Concrete Sequential, 10% Concrete Random	Step-by-step instructional guide, structured research
Sofia 50% Abstract Sequential, 50% Concrete Random	Structured research, Hands-on problem-solving task

This case study, on the other hand, has shown how effectively the ANN-WSM model can customize itself to suit specific learning styles, while ensuring instructional content is matched to strengths in cognition. Through the ability of ANN to recognize patterns and make decisions on a framework of WSM, this system adjusts recommendations in real-time to bring about better engagement and retention in learning. This serves to illustrate the great importance of personalized adaptive learning systems to the realization of efficient, sustainable, student-centered learning.

8. Evaluation

In order to assess the effectiveness of the ANN-WSM adaptive learning system that has been proposed, the evaluation used an educational software platform specifically designed for the practical, hands-on use of C++ programming among undergraduate students. There were 70 students in the introductory C++ course and interacted with the adaptive system chosen as the testbed over the 12-week period. The objective of the evaluation was to measure the ability of the system to provide personalized learning experiences, increase student engagement, and improve learning outcomes based on their cognitive styles.

The evaluation design followed a mixed-method experimental protocol combining quantitative performance metrics and qualitative feedback. Each metric – accuracy, pre-

cision, recall, F1-score, engagement score, learning retention rate, and performance improvement – was computed directly from log-level system data. Specifically, the ANN generated probabilistic predictions of preferred learning activities, which were subsequently refined and ranked through the WSM layer using expert-defined weights. This pipeline enabled us to trace, for every recommendation, how neural predictions translated into weighted scores, ensuring transparency in how results were derived. The scope of the evaluation was limited to a 12-week controlled study with 70 undergraduate participants in a C++ programming course, designed to measure short-term learning effectiveness and user engagement within a clearly defined domain.

8.1. Experimental Setup

The evaluation was conducted in a controlled learning environment where students accessed the C++ educational platform integrated with the ANN-WSM learning recommendation system. Each student was required to complete a series of programming exercises, coding challenges, and theoretical assessments. The system continuously adjusted the learning activity recommendations based on their learning style classification and engagement patterns. At the beginning of the study, each student underwent a learning style assessment based on the Gregorc Mind Styles Model. The ANN processed these classifications and generated an initial probability distribution of suitable learning activities. The WSM model then refined these probabilities to determine the most effective personalized learning paths. Throughout the 12-week period, the system dynamically adjusted its recommendations based on student performance, engagement levels, and feedback metrics. Each student participated in three different phases:

- (i) initial assessment through testing their previous knowledge of C++;
- (ii) adaptive learning phase, wherein the system provided the individual with personalized learning activities; and
- (iii) post-assessment evaluating profiling, engagement, and retention.

The evaluation and interpretation of the quantitative results (precision, recall, F1-score, engagement, retention, and performance improvement) were conducted by the research team based on data automatically recorded by the ANN-WSM system during the 12-week experimental period.

The system analyzed effectiveness by monitoring the time taken for exercises, exercise completion rates, quiz scores, and feedback by students.

8.2. Evaluation Metrics and Calculation of Results

The metrics reported in this section were computed based on the ANN-generated activity probabilities and their WSM-adjusted rankings, reflecting both predictive accuracy and pedagogical alignment. All performance metrics were calculated by the authors using the system's logged interaction data exported from the educational platform.

To evaluate the system's performance, we measured several key metrics:

- Accuracy of Learning Recommendations (ACC): The proportion of correctly assigned learning activities that aligned with students' cognitive preferences.

- Precision (P): The fraction of recommended activities that were actually useful and engaging for students.
- Recall (R): The proportion of relevant learning activities successfully recommended to students.
- F1-score: The harmonic mean of precision and recall, balancing accuracy and completeness.
- Engagement Score (ES): Measured as a weighted combination of time spent on activities, completion rates, and active participation in recommended tasks.
- Learning Retention Rate (LRR): The percentage of concepts retained over time, based on quiz scores after different intervals.
- Performance Improvement (PI): The increase in post-test scores compared to pre-test scores.

To enhance methodological transparency, each metric was computed directly from the system’s logged interactions, linking ANN predictions and WSM-based recommendations. The ANN first generated a probability distribution over potential learning activities for each student. The WSM then refined these probabilities using expert-assigned weights to yield the final ranked recommendation list. Accuracy, precision, recall, and F1-score were calculated by comparing these final ranked recommendations to the ground-truth activities that each student selected and reported as most engaging during the experiment. Engagement Score (ES) was derived as a weighted composite of task completion rate, time on task, and number of voluntary interactions. Learning Retention Rate (LRR) measured performance stability by comparing quiz scores across three assessment intervals. Performance Improvement (PI) represented the percentage increase between pre-test and post-test scores. Together, these metrics capture both algorithmic performance and pedagogical impact, providing a comprehensive evaluation of the ANN–WSM system.

The performance of the adaptive system was calculated using the following formulas:

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

where:

- TP (True Positives) represents correctly recommended activities that aligned with student preferences and resulted in improved engagement.
- FP (False Positives) represents recommended activities that did not align with student learning preferences.
- FN (False Negatives) represents relevant activities that were not recommended to the student.

Table 2 presents the aggregated results from the evaluation.

Table 2. Aggregated results from the evaluation.

	Metric
	Example
Accuracy of Learning Recommendations	87.5%
Precision	85.2%
Recall	81.7%
F1-score	83.4%
Engagement Score	82.3%
Learning Retention Rate	79.6%
Performance Improvement	18.2% increase

Note: Accuracy, precision, recall, and F1-score were derived from the ANN-WSM combined predictions; Engagement Score (ES), Learning Retention Rate (LRR), and Performance Improvement (PI) quantify behavioral and cognitive outcomes.

Results reveal that the ANN-WSM adaptive system achieved a very high sense of accuracy (87.5%) in facilitating the customization of learning recommendations to the needs of the individual student. While precision at 85.2% attests to the system's capacity for assigning meaningful and pleasurable learning activities, recall, at 81.7%, illustrates that significant intent activities were generally recommended. The F1 score, at 83.4%, combines the two and indicates an equal strength of the model in proposing anxiety concurrent with the varied needs of the learners. Engagement score: 82.3%, which stands for the uninterrupted ventures of the pupils in the recommended activities confirms the system's capability to elevate engagement and interactivity with the learning material. The learning retention score of about 79.6% indicates the styled learning paths or processes allow one to better retain knowledge over time. In addition, the performance improvement (18.2%) from pre-test to post-test scores attests that the adaptive learning proposition enhances the students' C++ programming prowess.

8.3. Discussion

The results, however, suggest that an important finding from the study was the relationship between adaptive learning pathways and knowledge retention, as longitudinal test tools such as surveys and formative and summative assessments show long-term retention rates to be better for students who engaged with content congruent with their style of learning. From these few findings, cognitive-based personalization may be the serviceable ingredient toward sustainability of learning outcomes over time.

These results are consistent with findings from related adaptive learning studies employing artificial neural networks or hybrid multi-criteria models. For example, Okewu et al. [8] and Borhani & Wong [9] also reported precision and recall values above 80%, indicating that ANN-based personalization can accurately model learner preferences. Similarly, Troussas et al. [29] achieved comparable gains in engagement and retention through hybrid inference mechanisms. Our observed 18.2% performance improvement aligns with the trend that ANN-driven adaptation enhances programming proficiency while maintaining pedagogical soundness. Collectively, these consistencies reinforce the validity of our ANN-WSM framework and confirm that its outcomes correspond closely with those of established research in adaptive educational systems.

Such a positive story does not come without the challenges and limitations appearing in the study. Some students had difficulty with the recommendations provided by the sys-

tem from the very beginning and had to be manually worked on by instructors to adjust their learning paths. Moreover, the model's functionality very much relied on the quality of the initial learning style assessment, which only underscores the need for further refinement in accuracy of classification. Future developments may consider continuously recalibrating learning style classifications to adapt to changes in student behavior and preferences over time. Another important aspect, in this case, is the further scalability of the system in the field, which in comparison to our research with the ANN-WSM methodology conducted on the controlled group of 70 students requires more optimization before it can be applied to larger platforms for education without increasing computational costs during real-time adaptivity. Future analyses should explore developing methodologies to simulate processing efficiency and improve the system's preparedness toward different populations of students.

This study further demonstrates the effectiveness of AI-led adaptive learning systems in higher education contexts. The ANN-WSM model provides a data-oriented, sustainable approach to personalized teaching, which will help boost student engagement, retention, and overall success in programming education. These findings point to a manageably extended research and development program for AI-based learning frameworks so that future learning environments remain flexible, inclusive, and successful.

9. User Experience and Feedback in Adaptive Learning

The efficiency of an adaptive learning system, thus, is not merely a function of how well its algorithms perform, but also of how well students and instructors engage the system and how satisfied they feel about it. How do students use the system? What other aspects about it are perceivable by them? What do they do from time to time that creates any sort of problems for them? These different aspects must be considered core in the model of learning, hence informing improvements with its design progress. This study used qualitative and quantitative feedback from students and instructors gathered throughout the 12-week evaluation period to assess the influence of ANN-based learning recommendations on engagement, motivation, and learning outcomes.

9.1. Student Feedback and Learning Experience

During the evaluation, students provided feedback on how well the system attunes itself to their individual learning styles, perceived usefulness of recommended activities, and engagement with C++ programming due to its adaptive nature. Surveys and structured interviews were carried out at the beginning, midpoint, and the end of the evaluation interval, giving students opportunities to reflect upon their experience throughout the evaluation period.

Most students reflected positively on the personalized recommendations, stating that, when compared to traditional static materials, the system offered them a more engaging alternative. Particularly there were many students classified as Abstract Random or Abstract Sequential learners who comprehended the process of learning theoretical concepts through collaborative recommendations and discussions due to interactive experiences imposed on the learning process. Even Concrete Sequential learners acknowledged the

utility of the structured exercises where they could go through coding tasks step-by-step aligned with their cognitive style.

On the other hand, for some students, open recommendation auto-processes were difficult in the beginning, mostly for those used to linear learning backed by a teacher. They stated the absence of a human teacher's explicit guidance and reported first periods of trial and error for deciding whether or not to place confidence in the recommendations made by the machine. However, by the middle of the study, other students had adapted to the system and were beginning to actively engage with the personalized learning activities, which meant that confidence in the recommendations given by AI was improving with prolonged using time.

On average, students offered the system an overall satisfaction level from 1 (very dissatisfied) to 5 (very satisfied) for a score of 4.3 out of 5, indicating that most of the learners found the system helpful in building their understanding of C++ concepts.

9.2. Instructor Feedback and Observations

Instructors participating in the study described very useful opinions about the real impact of ANN-WSM system in students progress and interactions in the classroom. Most of them mentioned the advantages of the adaptive system in that they were a great deal less involved in the manual assignment of activities, which allowed teachers to focus on helping students having problems with specific programming concepts.

Other major points noticed by the instructors were students' better autonomy and functioning on problem-solving skills. Since the system tailored activities to each student's learning style, the students carried out their learning increasingly by themselves because of less need for them to seek an instructor for repetitive clarifications. Participation of the students in the classrooms increased, according to the instructors, particularly among those hesitant to speak in discussions about coding.

However, some of the instructors noticed how a small group of the students would possibly need further support to adapt to personalized learning. A few students were not eager to diverge from conventional teaching; such students asked for assurance that AI-driven recommendations were valid. Some suggested that the installation of explanatory contents into the system would even help by providing brief reasons as to why specific activities were recommended, thereby increasing students' trust and confidence in the model.

9.3. Challenges Faced by Students and Instructors

Despite substantial gains in engagement and personalized learning by the ANN-WSM system, a few evaluation challenges did emerge. One of the most common struggles voiced by students is some rigidity of the recommended learning activities. This was particularly noted for those instances when the learner would prefer additional exploratory avenues beyond those mapped onto that individual's classified learning style. This became particularly visible among the blended cognitive style students, where, on occasions, the weights-fixed WSM approach fell short in capturing the subtle crests and troughs sometimes apparent in their learning preference over time. Another issue consisted of the reliance on the suggested activity types, in that some learners became dependent on activities prompted by their preferred style classifications and shied away from different

learning methods. According to the teachers, though there was high student commitment, certain students tended to avoid challenging themselves by going for something outside their main classification; this, they felt, ran the risk of limiting their exposure to diverse avenues for solving problems. That said, from a technical viewpoint, the real-time recommendation updates sometimes produced some activity recommendations that were redundant. In other words, rapid pacing through material enabled students to continue getting the same suggestions for activities. This shows the need for building in dynamic recalibration mechanisms for further versions of such systems—ones that would permit the model to adjust based on real-time learning behavior and not just for initial classification.

Incorporating brief explanatory content that clarifies why specific learning activities are recommended could further enhance user trust and engagement, especially for students accustomed to traditional instructor-led methods. Such transparency would strengthen acceptance of AI-driven personalization by making the recommendation process more interpretable and pedagogically reassuring.

9.4. Correlation Between User Satisfaction and ANN-Based Recommendations

To assess quantitatively how user satisfaction is related to the effectiveness of an ANN-based recommendation, statistical analysis was performed comparing engagement levels, learning performance, and satisfaction scores as reported. With a Pearson's correlation coefficient of 0.82, the relationship between engagement levels and satisfaction scores is deemed very strong evidence of a positive relation; that is, students who engaged more in the recommended activities were more likely to find it useful afterward. In terms of performance data, those students who did engage with their assigned learning activities showed an average score improvement of 18.2% from pre-test to post-test assessments, compared with only 10.4% improvement by students who generally failed to maximize their use of the personalized recommendations. These results confirm the ANN-WSM system not only helps students become more involved but also enhances learning performance, reaffirming its efficacy as an adaptive learning tool.

10. Conclusions

In this study, an adaptation learning system using artificial neural networks (ANNs) and the Weighted Sum Model (WSM) for a personalized and sustainable educational approach has been developed based on the Gregorc Mind Styles Model. The system will dynamically change learning activity recommendations based on cognitive styles, engagement patterns, and becoming new learning behaviors. The evaluation shows the advantages of the ANN-WSM that enhance learning personalization, encouraging student engagement, knowledge retention, and overall academic performance. The high accuracy of recommendations on learning material and the great uptick in performance for students prove that AI-powered adaptive learning systems can bring much to educational life, particularly in the arena of technical disciplines such as programming education. The results show that cognitive adaptation increased engagement and motivation, which allowed students to interact with content corresponding to their learning styles. The personalization of instructional material fits the way students advance through learning, taking into account their cognitive needs, allowing learning at a speed that maximizes the synergy between

knowledge about theory and hands-on experience. In addition, the dynamic nature of the system ensures that learning recommendations keep pace with learners by adapting itself according to learning progress, feedback, and changing cognitive preferences with time. A robust and scalable means of influencing learning intersubjective dynamics is enabled by the integration of ANNs for recognizing patterns and WSM for multi-criteria decision-making.

These notwithstanding, various limitations should be acknowledged: the overall efficacy of the system is strictly bound to the initial learning style classification system, which may not always adequately address the whole range of a student's cognitive preferences. Implementing continuous recalibration of learning style assessments could help the system adapt to evolving learner preferences over time, ensuring that recommendations remain aligned with actual behavioral and cognitive changes. While the Gregor Mind Styles Model provides a good framework for classification, human cognitive processing is nuanced, and this makes individual learning styles dynamic and susceptible to change over time. Future works could add a continuous learning style flexibility mechanism whereby the system improves the historical classification system over real-time use and on the basis of actual student engagement patterns. Another area of concern is that of scalability and computational efficiency. Whereas the framework has been shown to have good classification accuracy within a controlled testbed of 70 students, the deployment of any such system onto a larger scale like Massive Open Online Course (MOOCs) requires more optimization. The computational scheme of real-time ANN inference and WSM decision-making may inject latency into running the system with thousands of learners at once. Future works should explore distributed computing techniques, cloud-based AI deployment, and model compression strategies to smoothen and scale performance in more extensive academic settings. Although the initial rates of student engagement and retention have considerably improved, the study on long-term efficiencies of personalized recommendation still needs to be done. Conducting longitudinal studies to evaluate the long-term retention of knowledge and the sustained effectiveness of personalized recommendations would further strengthen the evidence base of the proposed model. Such studies could reveal how adaptive learning pathways influence learning persistence, motivation, and performance over extended academic cycles. The 12-week evaluation period gave proper insight into very short-term learning improvements; however, future research should address the effects of the system through extended academic cycles, looking directly into long-term retention of knowledge, responsiveness of different subjects, and overall stream of success into the following classes. Expanding the study to include diverse subjects, educational contexts, and learning domains would provide a more comprehensive understanding of the model's effectiveness and ensure its applicability beyond programming education. Finally, it could expand the dataset to technologically related disciplines apart from C++ programming.

Future work should explore integrating reinforcement learning with real-time feedback loops to enhance decision-making in the ANN-WSM framework. Such mechanisms would enable the system to learn continuously from student feedback and improve its recommendations dynamically. In this direction, future iterations could also adjust the WSM weights based on ongoing learner interactions, allowing the model to balance expert-defined pedagogical priorities with data-driven evidence. This adaptive weighting would refine personalization beyond static expert inputs. Moreover, incorporating multi-modal

learning data – such as eye-tracking, keystroke dynamics, or speech analysis – could further deepen insights into engagement and cognitive load. Overall, these extensions would make the ANN-WSM model more responsive, efficient, and scalable, advancing intelligent personalized education across diverse learning contexts.

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Christos Troussas is Assistant Professor in the Department of Informatics and Computer Engineering at the University of West Attica. He holds a PhD in Informatics and has extensive experience in personalization systems, human–computer interaction and AI-driven technologies. According to the Stanford University ranking, he has been repeatedly listed among the world’s top 2% of scientists.

Akrivi Krouska is Assistant Professor in the Department of Informatics and Computer Engineering at the University of West Attica. She received her PhD in Informatics from the University of Piraeus and has published widely on AI, multimedia applications, adaptive software and AR/VR systems.

Phivos Mylonas is Associate Professor in the Department of Informatics and Computer Engineering at the University of West Attica and earlier served senior research roles at NTUA. His research spans multimedia analysis, user modelling and intelligent systems.

Cleo Sgouropoulou holds a Diploma and a PhD in Electrical and Computer Engineering from NTUA and is Professor at the Department of Informatics and Computer Engineering, University of West Attica. Her research interests include software engineering, interoperability frameworks and learning technology systems.

Ioannis Voyiatzis is Head of the Department of Informatics and Computer Engineering at the University of West Attica. His research focuses on computer systems, data analytics, and software technologies.

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