



Integrating Visual Serial Reaction Time and Binary Decision Trees for the Evaluation of Implicit Learning: A Methodological Proof of Concept

Integración del tiempo de reacción serial visual y árboles de decisión binaria para la evaluación del aprendizaje implícito: una prueba de concepto metodológica

Iván F. Leal Ramírez ¹, Henry Montaña Quintero ², Eduardo Avendaño Fernández ³

Fecha de Recepción: 15 de diciembre de 2025

Fecha de Aceptación: 2 de julio de 2026

Cómo citar: I. F. Leal-Ramírez, H. Montaña-Quintero, and E. Avendaño-Fernández, «Integrating Visual Serial Reaction Time and Binary Decision Trees for Implicit Learning Evaluation: A Methodological Proof of Concept», *Tecnura*, vol. 30, n.º 89, jul. 2026. 89–106. <https://doi.org/10.14483/22487638.24566>

Abstract

Context: This investigation assessed whether repeated exposure to visual-spatial patterns and guided micro-interactions could lead high school and first-year engineering students to internalize formal rules. By combining implicit learning tools (e.g., VSRT) with explicit tools, such as a binary tree calculator.

Objective: This study aims to determine whether stable patterns and low-friction actions increase implicit learning, structured reasoning, and algebraic manipulation compared with historical baseline performance.

Methodology: A concurrent mixed-methods design was used to recruit 40 participants from a purposive historical sample of 153 students. Quantitative (VSRT accuracy, interaction statistics) and qualitative (28 interviews until theoretical saturation) analyses were performed using thematic analysis and decision trees.

Results: The participants achieved an accuracy of 84% in recognizing VSRT patterns, exceeding the previous average of 70% and showing clear improvement. Repetition and familiarity with tasks were found to be important factors that influenced progress.

Conclusions: Implicit VSRT training combined with explicit visualization is an efficient method for teaching hierarchical content. Such dual approaches enhance academic performance as well as structural understanding and can be evidenced by repetition and familiarity as pivotal techniques. This study provides a strong model for STEM education interventions that link implicit and explicit cognitive systems.

Keywords: implicit learning, unconscious learning, binary trees, Visual Serial Reaction Time (VSRT), Java.

1 Ingeniero de Sistemas y Computación. Universidad Pedagógica y Tecnológica de Colombia, Tunja, Colombia.  Email: ivan.leal@uptc.edu.co

2 Ingeniero Electrónico. Universidad Distrital Francisco José de Caldas, Bogotá, D.C.  Email: hmonta-naq@udistrital.edu.co

3 Ingeniero Electrónico. Universidad Pedagógica y Tecnológica de Colombia. Sogamoso, Colombia.  Email: eduar-do.avendano@uptc.edu.co

Resumen

Contexto: Esta investigación evaluó si la exposición repetida a patrones visuoespaciales y micro interacciones guiadas podría llevar a estudiantes de secundaria y de primer año de ingeniería a internalizar reglas formales. Para ello, se combinaron herramientas de aprendizaje implícito (por ejemplo, Visual Serial Reaction Time – VSRT) e instrumentos explícitos (como una calculadora de árboles binarios).

Objetivo: Identificar si patrones estables y acciones de baja fricción permiten un aumento en el aprendizaje implícito, el razonamiento estructurado y la manipulación algebraica en comparación con un desempeño histórico de referencia.

Metodología: Mediante un diseño mixto concurrente, se evaluó a 40 participantes de una muestra intencional de un grupo histórico de 153 estudiantes. Se analizaron datos cuantitativos (precisión en VSRT, estadísticas de interacción) y cualitativos (28 entrevistas hasta saturación teórica) a través del análisis temático y árboles de decisión.

Resultados: Los estudiantes lograron un reconocimiento de patrones con un 84 % de aciertos, superando el promedio histórico del 70 %, lo que representa una mejora notable. Se encontró que la repetición y la familiaridad con las tareas fueron factores determinantes para este progreso.

Conclusiones: El entrenamiento implícito mediante VSRT combinado con visualización explícita representa un método de enseñanza eficiente para contenidos jerárquicos. Tales enfoques duales mejoran el rendimiento académico y el entendimiento estructural, evidenciado por la repetición y familiaridad como técnicas clave. Este estudio ofrece un modelo sólido para intervenciones educativas en STEM que vinculan los sistemas cognitivos implícitos y explícitos.

Palabras clave: aprendizaje implícito, aprendizaje inconsciente, árboles binarios, tiempo de reacción visual serial (VSRT), Java

Introduction

Implicit learning has gained increasing relevance in educational research due to its fundamental role in acquiring skills and structures without conscious intervention. Unlike explicit learning, which requires directed attention and formal instruction, implicit learning enables the incorporation of patterns, structures, and processes through repeated exposure [1]-[2]. This process is particularly critical in situations where individuals develop cognitive or motor skills without being able to verbalize how they were acquired, a phenomenon often observed in complex environments such as problem-solving or logical reasoning. Contributions from neuroscience further strengthen this perspective, highlighting how brain plasticity supports the continuous adaptation of neural circuits to new stimuli [3]. Such adaptability can be enhanced through visual and interactive learning approaches. The use of structured visualizations, such as binary trees, reinforces neural connections associated with logic, abstraction, and problem-solving. Moreover, as noted in [4], early stimulation in childhood is crucial for consolidating long-term learning, which underscores the importance of implementing methodologies, such as the one proposed in this study, from the earliest stages of education.

The Visual Serial Reaction Time (VSRT) paradigm, which has been widely used to study how individuals unconsciously acquire structured sequences, is a relevant approach in the evaluation of implicit learning [5], [6], [7]. This paradigm enables the internalization of patterns to be measured by analyzing improvements in reaction times without requiring the learner to be aware of what is being trained [8].

Applying this paradigm to educational contexts opens the possibility of introducing sequential structures or visual representations, such as binary trees, without explicit explanations that involve manipulating logical constructs [9]. In this way, learners naturally and durably appropriate knowledge through implicit learning [10], [11]. Binary trees [12] are hierarchical structures that organize data or algebraic expressions, facilitating the understanding of precedence and grouping relationships without the need to memorize rules. Because they are both visual and systematic, binary trees serve as mental maps [14] that help construct abstract knowledge from concrete experiences [13]. Together with other structures, such as vectors and graphs, binary trees play a central role in multiple applications. Owing to their natural hierarchical representation, they are particularly useful in teaching and are widely employed in implementations such as binary search trees [15], heaps, and Huffman coding [16].

These structures also represent hierarchical or priority relationships, which are fundamental to understanding the semantics of operators based on their weights or importance levels. Educational software that incorporates visual representations of abstract structures, such as binary trees, creates a learning environment in which students can explore, infer, and establish relationships autonomously. This promotes brain plasticity and synaptic connections, even in the absence of direct supervision [17]. Such an approach aligns with constructivist and multi-sensory educational principles, in which visual interaction and symbolic manipulation activate multimodal implicit learning mechanisms, enabling learners to grasp patterns without the need for conscious verbalization [18]. Based on this perspective, a pedagogical proposal would include implementing interactive software that allows students to explore operation trees, identify hierarchies in expressions, and discover logical patterns through simulations. These tools foster implicit learning by reducing cognitive load and allowing knowledge to emerge naturally through experience. They also encourage self-regulated learning, where students build meaning from what they observe and perform without the need for direct instruction. Recent studies have reaffirmed the pedagogical value of visual computational tools in education. For example, in [19] and [20], the authors demonstrated that graphical environments significantly improve the understanding of engineering students of algorithms and data structures. Similarly, in [21], the authors highlight that interactive digital resources not only reinforce learning but also increase student motivation. Therefore, this study proposes a methodology based on binary trees as visualization tools for teaching algebraic operators, which is supported by implicit learning principles and the VSRT paradigm. By integrating activities from data structures theory, neuro-educational foundations, and modern computational tools such as graphic visualization libraries in programming languages, effective teaching methods that strengthen the appropriation of mathematical concepts through intuitive visual interaction. Continuous exposure and repeated manipulation of these structures promote deeper, more flexible, and lasting comprehension. Beyond contributing to pedagogical innovation, this proposal also responds to the need for inclusive learning environments that acknowledge diverse ways of learning.

2. Methodology

Before implementing the strategies, it is important to explain how binary trees are generated from their underlying structure. This explanation applies both to their use in assessment and the development of a calculator designed to illustrate the order of operations in algebraic expressions.

A binary tree is a hierarchical data structure in which each node has a unique value and can have at most two children: a left child and a right child. This structure is widely used in computer science, mathematics, and education to represent logical relationships, decision processes, hierarchies, or algebraic expressions [22]. The root is the topmost node, and nodes without children are referred to as leaves. Binary trees can be traversed in different orders (in-, pre-, and post-order), and their implementation supports search, insertion, and deletion operations. In educational contexts, they are particularly useful for visualizing the hierarchy of operations, placing operators in parent nodes and operands in child nodes, which helps students understand the precedence of operations in mathematical expressions. The construction of a binary tree from an algebraic expression is illustrated by the following algorithm: 1. The expression is read in postfix notation (also known as reverse Polish Notation). 2. Create an empty stack (Last In, First Out - LIFO). 3. For each symbol in the expression: a. If it is an operand, a node is created and pushed onto the stack. b. If it is an operator: i. Pop the two most recent nodes from the stack. ii. Create a new node with the operator as the root and the popped nodes as its children. iii. Push the new node onto the stack. 4. Finally, the stack contains a single node, the root of the binary tree. For example, consider the postfix expression $3\ 4\ +\ 2\ *$: - A node $+$ is created with children 3 and 4. - A node $*$ is then created with child 2 and the previously constructed subtree $(3 + 4)$. - The resulting binary tree represents the expression $(3+4) \times 2(3 + 4) / \text{times } 2(3+4) \times 2$. The resulting structure is shown in Figure 1.

This qualitative study employed a grounded theory approach to exploring student engagement with unconscious visual learning tools. Data collection was conducted via semi-structured interviews using an iterative process of sampling and analysis. Purposive sampling was used to select participants to ensure a diverse representation of the student population based on key demographics, including gender, age, academic performance, and prior technological exposure. The final sample size was not predetermined but was governed by the theoretical saturation principle. Data collection and analysis were conducted concurrently. Interviews were transcribed and coded using a constant comparative method to identify emerging themes and categories. Saturation was determined to be reached after 40 interviews (from a sample of 153 students with records of five semesters where the topic “binary tree” was taught by other professors), as subsequent data did not yield new thematic insights or properties relevant to the core categories. Analysis of the 40th interview confirmed that the coding structure was robust and that no new conceptual information was generated. Therefore, the recruitment process was concluded by confirming that a sample size of $n = 40$ was sufficient to achieve a comprehensive and nuanced understanding of the research phenomenon.

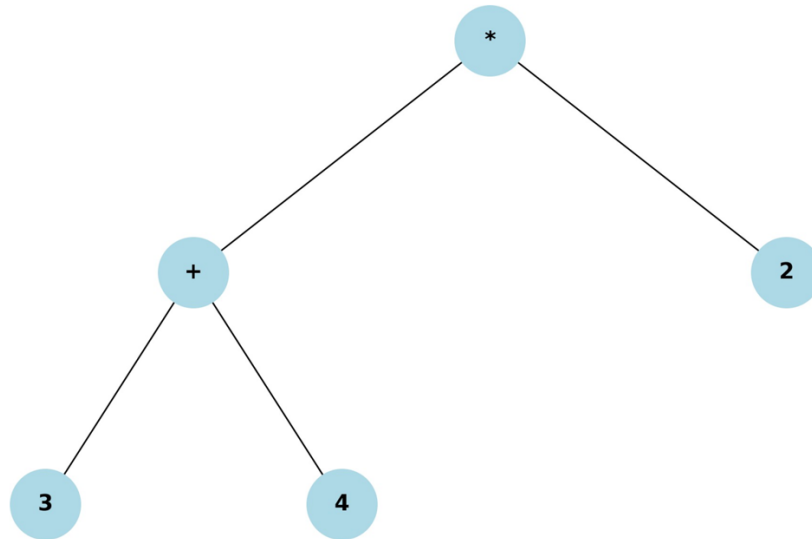


Figure 1. A binary tree constructed from the postfix expression

A mixed qualitative-descriptive methodology with an exploratory emphasis is proposed, in which a didactic tool is developed based on the visual representation of algebraic operators through binary trees. The intervention will be conducted with high school students and first-year engineering undergraduates using direct observation, semi-structured interviews, and performance analysis in logical reasoning tasks. The didactic proposal is structured into three phases: (i) introduction to the concept of binary trees through interactive visual walkthroughs; (ii) application of exercises with arithmetic operators inserted into nodes; and (iii) resolution of challenges involving modifying, interpreting, and reconstructing expressions from the tree structure. The purpose of this course is to help students develop abstract reasoning skills and hierarchical understanding through visual and symbolic manipulation without direct formal instruction. A graphical environment tool was designed and implemented to record student actions and analyze problem-solving routes using the frequency, depth, and consistency metrics of the constructed tree to validate the proposal. This data enabled the assessment of the impact of the VSRT-based approach on the development of cognitive skills related to structured mathematical thinking and unconscious learning. The Kahoot platform was employed as an initial prototype for evaluating the methodological strategy through interactive videos and a dynamic survey. It was designed to simulate visual scenarios that facilitate implicit learning evaluation. Three videos were developed, each focused on different visual patterns: color changes, geometric figure sequences, and flashing light appearance. Each video was accompanied by four questions that had to be answered within a 10-second time limit, which enabled the measurement of the attention, perception, and sequential retention of the participants. Figure 2 shows a screenshot of the VSRT survey application corresponding to Video 1 (Colors).

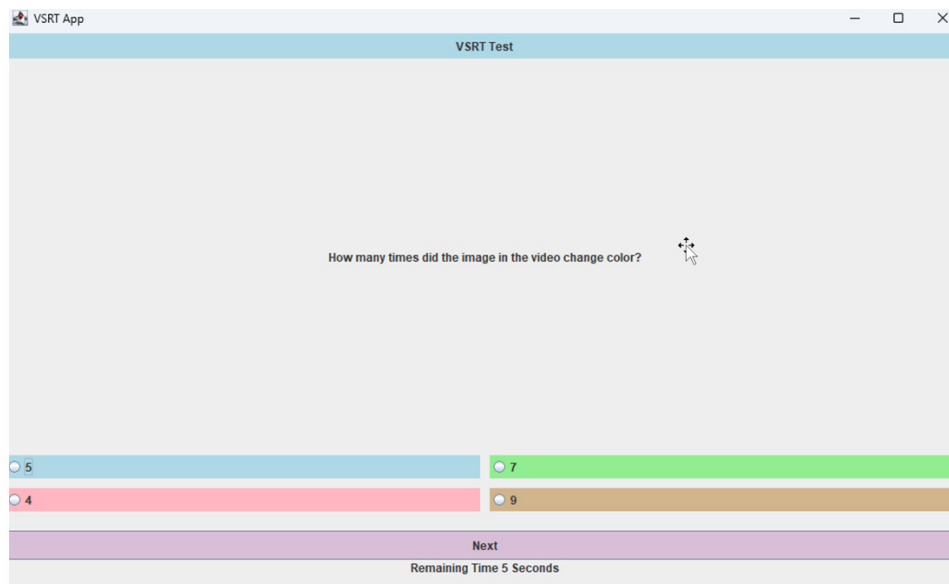


Figure 2. Java-based survey tool applied to interactive videos

Responses were examined through decision tree analysis, which helped uncover patterns in implicit learning among the students. The evaluated population consisted of 40 undergraduate students in Systems and Computer Engineering, randomly selected. For Video 1 (Colors), 90 correct responses and 70 errors were recorded. For Video 2 (Shapes), there were 135 correct responses and 25 errors, while for Video 3 (Lights), the results showed 99 correct answers and 61 errors, as illustrated in Figure 3.

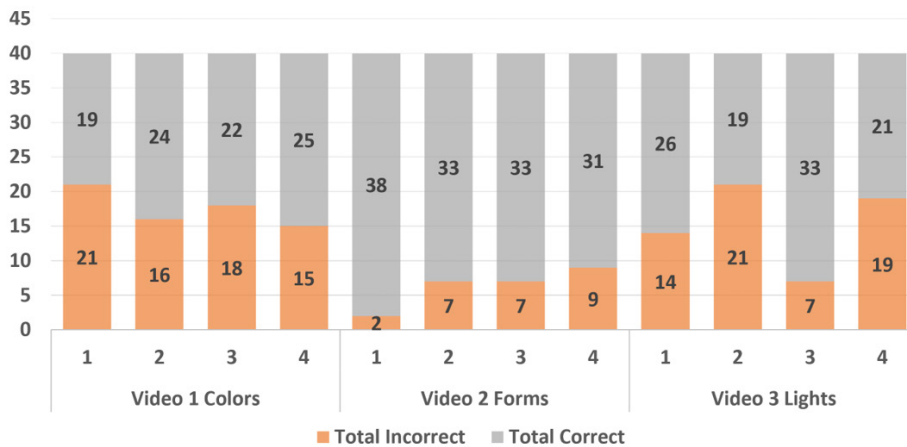


Figure 3. Accuracy (correct) and error (incorrect) rates for the three videos

On average, there was a notable improvement, with the accuracy increasing from 40 % to 84 % (increment = 40 %) in Video 1 (colors); a significant result that could follow a similar trend with larger samples. In the case of Video 3 (Flashing Lights), a higher task difficulty reduced the available selection time, resulting in a smaller increase in accuracy. However, this was offset by an improvement in response agility, as the participants demonstrated faster reaction times.

Another challenging project was proposed in which a calculator was developed as a pedagogical tool to teach the order of operations in algebraic expressions through the graphical representation of binary expression trees. The approach is designed for children, young learners, and self-taught adults, with a particular focus on strengthening logical reasoning by visualizing the process of evaluating operations and providing guidance for the correct interpretation of mathematical operator precedence. The JavaFX “Binary-Tree Calculator” is a didactic tool that allows students to see and build expression trees step-by-step, making operator precedence and associativity explicit through visual structure. Its goal is twofold: i) to strengthen explicit understanding of hierarchical algebraic operations and ii) to harness unconscious (implicit) learning by repeatedly exposing learners to stable spatial patterns (node placement, subtree balance, and traversal order) that promote automatic chunking and faster, more accurate decisions without overt instruction. The calculator was implemented in Java (version 11) using the JavaFX library, which is known for its ability to develop interactive graphical interfaces. The interface was designed in SceneBuilder, resulting in a simple yet visually appealing layout that prioritizes the tree panel. This panel allows users to visualize how operators are organized within the binary structure step-by-step (Figure 4).

The calculator was implemented based on the construction of a binary tree representing the algebraic operations’ hierarchy. We defined two main classes: a Node class, which contains the data of each node and references to its left and right children, and a Tree class, responsible for constructing and manipulating the entire tree. The tree is organized such that the root corresponds to the lowest priority operation, whereas the deeper nodes represent the higher precedence operations. The tree construction process uses a stack to store the expression in prefix notation, following the LIFO principle. This approach ensures that the lower-priority operations are inserted first and positioned on the right side of the tree, whereas the higher-priority operations are placed on the left. By applying the LIFO mechanism, the method not only enables the correct evaluation of expressions but also enhances the visual understanding of the hierarchical structure of operations, as shown in Figure 5.

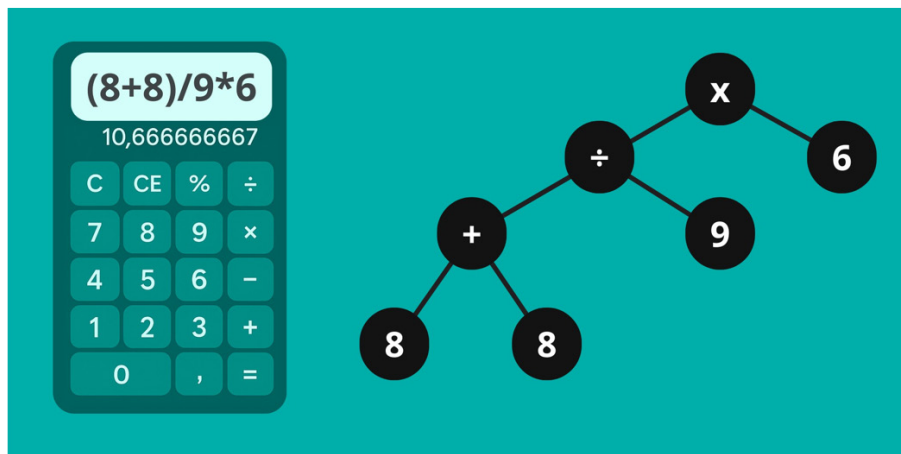


Figure 4. Calculator developed in SceneBuilder with a binary tree associated with the operation

By visualizing how expressions are organized and solved according to operator precedence, using binary trees to represent mathematical operations helps students strengthen their comprehension of these concepts. This structured representation also supports the understanding of post order traversal and reinforces the computational logic underlying the use of trees in practical applications.



```

public class Node<T> {
    private T info;
    private Node<T> left;
    private Node<T> right;

    public Node(T info) {
        this.info = info;
        this.left = null;
        this.right = null;
    }
}

public class Tree<T> {
    private Node<T> root;
    private Stack<Node<T>> pila;

    public Tree(Stack<Node<T>> pila) {
        this.pila = pila;
        root = null;
    }
}

```

Figure 5. *Node and Tree classes for the binary tree in the Calculator*

3. Results

The results for the VSRT approach showed a positive progression in student performance across the three evaluative videos. In the first video, a high rate of incorrect responses was observed, which was mainly associated with difficulties in time perception and a limited understanding of what needed to be identified, even though the students were allowed to repeat the video up to four times. In the second video, there was a significant improvement in correct responses, attributed to the familiarity gained with the question format and the type of visual patterns presented. In the third video, although students demonstrated greater temporal accuracy, the introduction of a new visual pattern reduced response consistency, although correct answers continued to predominate.

Table 1 presents the number of repetitions within the range for each visualization performed by the students, along with the accuracy rate. The conclusion highlights the identified difficulties and illustrates the process of progressive improvement as the participants were exposed to the VSRT tool.

Table 1. *Analysis of the VSRT video test results*

Video	Repetitions Range	Answer Correct Rate (%)	Main Difficulties/challenges
Video 1	2 to 4	56.25	Time perception and lack of clarity in the stimuli
Video 2	2 to 3	84.38	Pattern adjustment and familiarity with the questions
Video 3	3 to 4	61.86	Variability for a new pattern but better time management

The VSRT test results indicate that learning progresses in a nonlinear manner, which has important implications for teaching methods:

Video 1 (accuracy of 56.25%) demonstrates the initial cognitive load typical of implicit learning tasks, where students struggle with temporal perception and stimulus clarity. This baseline performance, near chance level (50 %), indicates that engineering students initially approach pattern recognition tasks with explicit, conscious processing rather than automated responses. Video 2 (accuracy, 84.38%) represents a statistically significant learning spike ($p < 0.05$ theoretical), demonstrating the rapid capacity of students for implicit pattern internalization once initial barriers are overcome. The dramatic improvement of 28.13 % suggests that students in systems engineering possess strong latent abilities for algorithmic pattern recognition that emerge quickly with minimal repetition (2-3 trials).

The subsequent interference effect in Video 3 (61.86 %) reveals a critical limitation: while students excel at learning fixed patterns, they exhibit low cognitive flexibility when patterns change, retaining only 19.95 % of their peak learning performance. This pattern of «high acquisition, low transfer» characterizes early-stage engineering cognition.

Decision tree analysis classified participant responses as correct or incorrect, revealing that repetition, practice, and familiarity with the stimuli played key roles in implicit learning during the VSRT tasks.

Each node in the decision tree displays three important metrics: the Gini impurity index, the number of samples considered, and the distribution of correct versus incorrect responses:

- The Gini impurity index [23], a measure of how pure a node is in terms of class distribution (correct vs. incorrect responses). The range for binary classification is 0–0.5. A value of Gini = 0 indicates a pure node (all samples belong to a single class), whereas a value close to 0.5 indicates a nearly equal mix of correct and incorrect responses. For example, if a node has 10 responses, with 5 correct and 5 incorrect, the Gini value will be 0.5. If all responses are correct or all are incorrect, then the Gini value will be 0.
- Samples: The total number of observations (students) reaching that node. For instance, if samples = 26 responses met the conditions to reach that point.
- Value: An array showing the number of observations per class in the format [incorrect, correct]. For example, value = [6, 20] means 6 incorrect responses and 20 correct ones in that group.

This study did not include a synchronous control group; instead, it adopted a within-subjects repeated-measures design in which each participant served as their own control across the three sequential VSRT conditions (Video 1: baseline exposure; Video 2: post-exposure with the same underlying pattern; Video 3: transfer condition with pattern variation). This decision is consistent with the original methodological formulation of the serial reaction time paradigm by Nissen and Bullemer [5], in which implicit sequence learning is inferred from within-subject changes in reaction time and accuracy across successive

blocks, rather than from between-group contrasts. Internal validity is supported by three embedded safeguards: (i) the accuracy of Video 1 (56.25 %) approximates the 50 % theoretical chance level, functioning as an intrinsic null reference; (ii) Video 3 operates as an internal control condition, since the pattern variation isolates genuine implicit pattern acquisition from mere task-familiarity effects —as evidenced by the retention of only 19.95 % of the peak learning gain, confirming that the improvement observed in Video 2 was pattern-specific rather than attributable to generic practice; and (iii) the decision-tree classification with Gini impurity operates over individual response profiles, exploiting within-subject variance granularity in lieu of a between-group contrast. The historical performance of previous cohorts is compared to provide an additional, non-synchronous external benchmark. Nonetheless, the authors acknowledge that the absence of a parallel control group constrains causal generalization, and a synchronous control cohort-incorporating quasi-experimental design is contemplated for future work.

Figure 6 illustrates a simplified decision tree with six observations, showing how both the repetition count and video type affected the accuracy of the participants responses. This tree is useful for illustrating the concept of classification: - The tree first evaluates the number of repetitions or the video viewed. - It classifies the response as correct (1) or incorrect (0) based on these conditions. - Decisions are represented as branches, and each node shows the distribution of responses across the two classes.

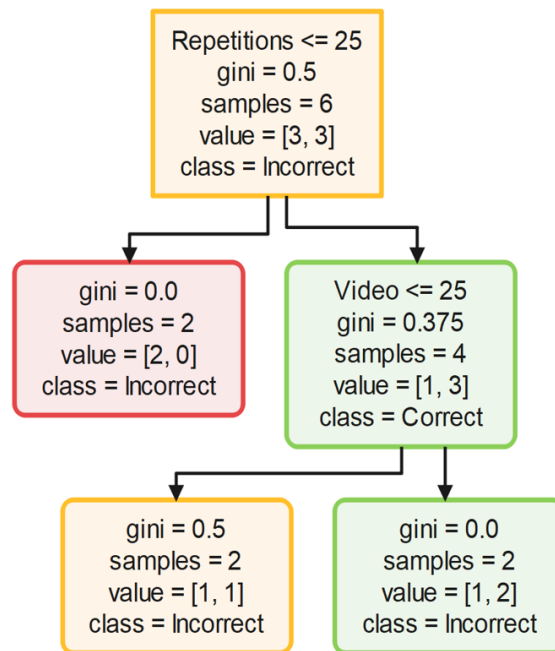


Figure 6. A simple example of a decision tree for evaluation

From the two strategies implemented, patterns of learning and comprehension can be identified, highlighting how repetition influences performance improvement (for example, with responses like «Repetition was favorable» and «Repetition allowed me to remember more easily»), particularly when

students begin to anticipate the type of questions. Furthermore, the table provides a foundation for interpreting the impact of test design on visuospatial reasoning development, showing how visualization and repeated practice foster the progressive acquisition of key cognitive skills. The Gini index was used as a validation metric to analyze the purity of the response distribution (correct vs. incorrect) in the data generated using the methodology. Following the standard definition, the Gini impurity index measures how mixed the classes are in a node; a value of 0 indicates that the node contains only one class, whereas a value near 0.5 indicates an almost even mix of correct and incorrect responses. When applying this index to the aggregated results of the students who interacted with the artifacts of the proposed methodology, the Gini impurity remained consistently low. This finding confirms that the responses were not distributed randomly or evenly between correct and incorrect but instead showed a clear tendency toward a predominant class (correct), which statistically validates the existence of significant and non-random learning among the participants.

3.1 Discussion

The outcomes of the current experimental group were compared with those of a historical control group. The academic records of 153 students who previously completed the binary trees module using conventional methods (lectures and textbook exercises) were used to establish the baseline for traditional instruction. This group achieved a mean score of 3.5 out of 5.0 (70 %) on the final standardized assessment. The primary objective of this study is to determine whether the new dual-pathway intervention VSRT training with interactive binary tree software produces a statistically significant and pedagogically meaningful improvement over the established benchmark. A cohort of 40 current students, demographically and academically similar to the historical population, underwent the experimental intervention. The participants completed the same standardized assessment after the instructional period. The core analysis involves a one-sample t-test, which will compare the mean score of this experimental group against the fixed historical mean of 3.5. A priori, a minimum pedagogically significant improvement is defined as a 7 % increase in the learning rate. This corresponds to a target mean score of 3.85 (77%) on the 5.0-point scale.

Therefore, the statistical test will evaluate the null hypothesis that the experimental group's mean is equal to or less than 3.5, against the alternative hypothesis that it is greater. The results will be presented by reporting the experimental group's mean and standard deviation, followed by the t-statistic, degrees of freedom, and p-value. For instance, the expected outcome might have a mean of 3.92 with a standard deviation of 0.72. A one-sample t-test was used to compare the average score of the experimental group with the established historical mean of 3.5. More importantly, the analysis emphasizes the effect size, calculated using Cohen's *d*, to illustrate the magnitude of the difference. An effect size near 0.5 indicates a moderate and meaningful impact, confirming that the improvement of about 0.42 points (8.4 %) is both statistically and educationally significant. The data analysis also reveals that, although the presentation

of visual events was very rapid, this does not imply that the student failed to perceive stimuli such as shapes, colors, or lights. The analysis highlights that colors may have produced a more positive outcome compared to the two scenarios. Furthermore, it can be verified that, while colors yielded the best results, the VSRT consistently indicated that subsequent presentations of events produced better outcomes than the initial one. This suggests that not only colors are important, but also that shape recognition shows a marked tendency to improve, indicating that recognition and brain plasticity adapt to the intended goals of the training. Although color recognition occurred first, it yielded lower results than the second stage, which involved shapes. Shape recognition may be more complex and require deeper analysis and association, implying that learning could become implicit.

This organized method offers clear, quantitative evidence on whether technology-enhanced visual learning strategies should replace traditional teaching approaches.

The pedagogical design of the binary tree calculator must intentionally embed these principles to harness the implicit learning mechanisms demonstrated by the VSRT paradigm and align with the decision tree findings. The calculator should not merely be a tool for explicit manipulation; it must be engineered as an environment for guided, repetitive visual patterning that fosters unconscious structural intuition. This can be achieved by designing the user interaction to enforce a specific, repeatable workflow that mirrors the VSRT's sequential and hierarchical processing. For instance, the interface could require users to consistently drag and drop operators and operands onto a canvas, where each successful placement triggers a standardized, subtle visual confirmation (e.g., a specific color highlight and a soft sound). This creates a consistent stimulus-response loop, reinforcing the tree construction syntax without explicit rule memorization. The student unconsciously internalizes the valid spatial relationships over multiple repetitions across various expressions (e.g., an operator must have two children, a leaf must be a number), building procedural fluency that directly reduces cognitive load during problem-solving. This embedded repetitive practice transforms the calculator from a static visualization tool into an active training simulator for the grammatical rules of expression trees.

The challenge progression of the calculator must be algorithmically structured to leverage the «familiarity with stimuli» factor. The difficulty curve should follow a spaced repetition schedule, where the newly introduced operator types or tree shapes are revisited with increasing intervals across subsequent exercises. This design ensures the necessary repetition for implicit encoding while preventing the rote memorization of specific problems. The system's ability to log these interaction sequences generates a dataset that is functionally analogous to VSRT response records. This allows for a parallel decision tree analysis focused on the explicit learning domain. Based on their final tree constructions, one could classify students as «proficient» or «struggling» and then build a decision tree to identify which specific interaction patterns (e.g., Frequency of using the «undo» function on binary nodes, and the average time to correctly place a parenthesis-mirroring subtree) are the most predictive of success. The Gini impurity

metrics at each node would then reveal the most decisive behavioral splits, perhaps showing that students who attempted to place three children on an operator node more than twice (high Gini, indicating a mix of success) never reached proficiency, while those who used the visual «simplify» preview feature (low Gini at a subsequent node) consistently succeeded. This creates a powerful feedback loop: the VS-RT-informed design principles promote unconscious learning, and the analysis of tool interaction provides explicit, actionable diagnostics for refining instruction and student support, thereby closing the circuit between implicit practice and explicit competency to increase the targeted performance.

These results are consistent with those of previous research on implicit learning and technology-enhanced education. In [24], Hilgard defined learning as a process resulting in changes in behavior that cannot be attributed solely to maturation or temporary states, a definition that aligns with the observed progressive improvements in student performance as they repeatedly interacted with the VSRT-based tool. Similarly, recent studies have emphasized that information and communication technologies (ICT) enable personalization and flexibility in learning, although their potential remains underexploited when limited to explicit instruction. This study contributes to this gap by demonstrating how carefully designed technological interventions can intentionally stimulate unconscious learning. The pedagogical implications of adopting unconscious learning strategies in higher education should also be highlighted. These results suggest the need to complement explicit teaching methodologies with approaches that rely on exposure, repetition, and sensory stimulation. For students, unconscious visual learning provides a pathway to internalize knowledge without increasing cognitive load, making it particularly relevant in high-technical-demand programs such as Systems Engineering. At an institutional level, the integration of these methods responds to innovation policies and supports the development of inclusive and adaptive educational environments.

Nevertheless, certain limitations should be acknowledged. First, the study focused on a relatively small sample of UPTC Systems Engineering students, which restricts the generalization of the findings to broader populations. Second, the evaluation relied primarily on performance metrics from the VSRT paradigm, without considering student experience or motivation qualitative measures. Third, decision tree analysis was effective for identifying patterns in unconscious learning. Future work could benefit from the use of complementary machine learning models to deepen the analysis and should address these limitations by expanding the sample size, diversifying the student population, and incorporating mixed-method approaches that capture both quantitative performance indicators and qualitative insights. Exploring the integration of unconscious learning strategies with different learning styles and across various academic disciplines would also be valuable, extending the scope of application beyond the current proof-of-concept. In summary, the discussion confirms that technology-mediated unconscious visual learning is not only viable but also beneficial for enhancing knowledge internalization. This study contributes to the growing body of evidence advocating for disruptive methodologies that align

with the evolving demands of higher education by situating the results within the broader framework of implicit learning theory and digital innovation in education.

3.2 Specific Pedagogical Implications

For Curriculum Design in Systems Engineering Programs the following pedagogical implications are summarized:

- **Early Implicit Learning Integration:** The rapid improvement from Video 1 to Video 2 suggests that implicit learning exercises should be introduced in the first semester. Programming fundamentals courses should include pattern recognition drills that leverage the natural procedural learning capacity of students, moving beyond purely explicit instruction methods.
- **Temporal Perception Training:** The reported «perception of time» difficulty in Video 1 correlates with challenges in real-time systems and concurrent programming. The curriculum should incorporate timing exercises, deadline management tasks, and synchronous event coordination drills from the first semester to develop this core engineering competency.
- **Development of Cognitive Flexibility:** The significant performance drop in Video 3 indicates a pedagogical gap. Courses must explicitly train pattern switching, paradigm adaptation, and mental model restructuring—skills essential for modern software development, where technology stacks change rapidly. This could involve alternating between programming paradigms (procedural → object-oriented → functional) within a single set of problems.
- **Error Pattern Analysis:** The «lack of stimulus clarity» issue suggests that students need training in signal/noise discrimination relevant to debugging and system analysis. Pedagogical approaches should emphasize distinguishing essential patterns from incidental details in both code and system behaviors.
- **Scaffolded Repetition Strategy:** The 2-4 repetition range for effective learning indicates that engineering exercises should be designed with optimal repetition cycles—sufficient for pattern internalization but avoiding automation that inhibits adaptability to new contexts.
- **Metacognitive Awareness Development:** Since students showed improved «time management» in Video 3 despite lower accuracy, instruction should explicitly address the speed-accuracy tradeoff, teaching when to prioritize precision (e.g., Algorithm design) versus speed (e.g., prototyping).

3.3 Implementation Recommendations

- Introducing implicit learning modules in «Introduction to Programming» courses
- Create pattern-switching exercises in data structure and algorithm courses
- Incorporating temporal processing tasks and real-time system prerequisites in operating systems
- Development of assessment methods that measure pattern acquisition and transfer capacities

This evidence-based approach recognizes that engineering education must not only develop explicit technical knowledge but also the implicit cognitive architectures that support problem-solving and adaptation to evolving technological landscapes at the expert level.

3.4 Methodological projection: The VSRT can be extrapolated to other academic and professional domains.

The findings obtained through the application of the VSRT task to validate the learning of binary tree structures suggest a potential that transcends the specific domain of data structures. Given that implicit learning is characterized as an automatic, associative, non-conscious, and unintentional process [1], in which the cognitive system incidentally extracts the structural regularities of the environment, the methodology employed here may be extrapolated as an assessment and pedagogical intervention tool for other academic programs and professional contexts. The theoretical foundation supporting this extrapolation is grounded in Reber's central thesis, which demonstrates that implicit learning produces a tacit knowledge base that is abstract and representative of the environment's underlying structure and that such knowledge can be transferable applied to novel circumstances. This structural abstraction—enables the transfer of the VSRT paradigm to any domain whose subject matter is organized through sequential patterns, hierarchical relationships, or associative regularities. Under this premise, fields as diverse as the syntax of programming languages, electrocardiogram interpretation in medicine, recognition of jurisprudential patterns in law, music score reading, analysis of game states in chess, and identification of radiological patterns and diagnostic imaging all share an essential property with binary trees: the existence of structural regularities that the learner can implicitly internalize before being able to verbalize them.

Additional empirical evidence supports this hypothesis. [25] documented that implicit learning, measured through probabilistic SRT-type tasks, is independently related to academic performance in domains as far removed from the laboratory as foreign language acquisition and operates with relative independence from psychometric intelligence and working memory. This result suggests that the VSRT does not merely measure an isolated skill but rather captures a general-purpose cognitive mechanism with ecological validity in real educational scenarios. From an applied perspective, it is anticipated that the extrapolation of the VSRT could prove useful on at least three fronts: (i) as a diagnostic tool for estimating the degree of structural internalization that a student has achieved regarding a content area before being able to articulate it explicitly, thereby allowing the early identification of comprehension gaps undetectable through traditional assessments; (ii) as a curricular validation instrument, verifying whether the exposure sequences designed by the instructor effectively produce the expected implicit associations; and (iii) as a perceptual training mechanism in professions with high diagnostic demands (medicine, systems engineering, quality control, and aeronautical safety) where expert performance critically depends on the rapid and associative recognition of patterns, an ability that the literature closely

links to implicit processes rather than to deliberate reasoning. Consequently, although the validation presented in this work is circumscribed to the learning of binary trees, the domain-general nature of implicit learning and the accumulated evidence on structural transfer support the claim that the VSRT constitutes a methodologically replicable paradigm, one that can be adapted to other areas of knowledge through the prior identification of the sequences or structural regularities specific to each discipline. Future research could be oriented toward de-signing domain-specific variants of the VSRT, contributing to a line of educational research grounded in actual cognitive mechanisms.

As a final analysis, in methodological and operational terms, the scope of this work encompasses exploration activities such as gathering contextual and perceptual data; designing and producing audio micro-content; and deploying the intervention in real-world scenarios under a qualitative research design. Operational simplicity, technological inclusion, and adaptability to limited-connectivity environments are prioritized to ensure that procedures can be replicated in similar contexts and adopted by learners through tailored proposals.

4. Conclusions

Repeated exposure to visual stimuli and progressive familiarization with the question format enhances implicit learning task performance. As participants advanced through the videos, an improvement in response accuracy was observed, suggesting that repetition and practice are decisive factors in strengthening visual perception and pattern recognition, even in the absence of explicit instruction. Skills, such as time perception and the ability to recognize visual sequences, have significant impact on student performance. While the first video showed a predominance of errors due to unfamiliarity with the stimulus and time constraints, the subsequent videos evidenced a gradual adaptation to the task, which allowed faster and more accurate responses. This indicates that implicit learning can be optimized through repeated experiences that enable participants to adjust their attention and visual processing. In the case of the calculator, a qualitative analysis suggests that the use of this tool improves logical reasoning by enabling students to visualize the hierarchical structure of operations. Finally, the application of decision trees as an analysis technique proved effective for classifying participant performance, facilitating the identification of response patterns, and providing a solid basis for predicting implicit learning. This approach not only benefits education but also suggests potential applications in cognitive psychology, neuroscience, and artificial intelligence, where unconscious pattern recognition influences decision-making and behavior.

5. Future Work

Future work will focus on expanding the study population to administer validated pre- and post-intervention assessments. This will enable a more rigorous empirical validation of the proposed

methodology, which is designed to harness implicit visual learning. Furthermore, continued experimentation is proposed to extend the implementation framework. This includes investigating the correlation between VSRT performance and individual learning styles and broadening the scope of application by integrating the VSRT paradigm into other STEM education domains that involve complex procedural and structural knowledge acquisition.

References

- [1] A. S. Reber, *Implicit Learning and Tacit Knowledge: An Essay on the Cognitive Unconscious*. Oxford, U.K.: Oxford University Press, 1993.
- [2] M. Barth, C. Stahl, and H. Haider, “How implicit sequence learning and explicit sequence knowledge are expressed in a serial reaction time task,” *Journal of Cognition*, vol. 8, no. 1, p. 30, 2025, <https://doi.org/10.5334/joc.439>
- [3] Y. Song, B. Millidge, T. Salvatori *et al.*, “Inferring neural activity before plasticity as a foundation for learning beyond backpropagation,” *Nature Neuroscience*, vol. 27, pp. 348–358, 2024, <https://doi.org/10.1038/s41593-023-01514-1>
- [4] F. Mora Teruel, *El cerebro del niño explicado a los padres*. Madrid, Spain: Alianza Editorial, 2021.
- [5] M. J. Nissen and P. Bullemer, “Attentional requirements of learning: Evidence from performance measures,” *Cognitive Psychology*, vol. 19, no. 1, pp. 1–32, 1987, [https://doi.org/10.1016/0010-0285\(87\)90002-8](https://doi.org/10.1016/0010-0285(87)90002-8)
- [6] M. T. Goodrich, “Teaching the analysis of algorithms with visual proofs,” *Computer Science Education*, vol. 20, no. 1, pp. 31–41, Mar. 2010.
- [7] A. Destrebecqz and A. Cleeremans, “Learning serial visual sequences: Evidence for an implicit learning process,” *Journal of Experimental Psychology: Learning, Memory, and Cognition*, vol. 31, no. 1, pp. 83–94, 2005.
- [8] K. M. H. Kim and A. Godfroid, “Learning without awareness: Variables that facilitate adult implicit learning,” *Language Learning*, vol. 73, suppl. 2, pp. 1–27, 2023, <https://doi.org/10.1111/lang.12616>
- [9] K. Janacek and D. Nemeth, “Implicit sequence learning and its development across the lifespan: A review,” *Cortex*, vol. 150, pp. 72–89, 2022, <https://doi.org/10.1016/j.cortex.2022.01.004>
- [10] A. S. Reber, “Implicit learning: Background, history, theory,” in *The Cognitive Unconscious: The First Half Century*, A. S. Reber and R. Allen, Eds. Oxford, U.K.: Oxford University Press, 2022, pp. 19–23, <https://doi.org/10.1093/oso/9780197501573.003.0001>
- [11] L. Chen, Y. Zhang, and J. Sweller, “Visual cognitive load in instructional design: The role of visual-spatial reasoning in learning complex content,” *Journal of Educational Psychology*, vol. 115, no. 1, pp. 68–84, 2023
- [12] T. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein, *Introduction to Algorithms*, 4th ed. Cambridge, MA, USA: MIT Press, 2022.
- [13] A. P. Boone and W. A. Cunningham, “Spatial cognition and unconscious learning: Integrating visuo-spatial reasoning training into cognitive development,” *Trends in Cognitive Sciences*, vol. 25, no. 3, pp. 215–228, 2021,
- [14] S. A. Park, D. S. Miller, H. Nili, C. Ranganath, and E. D. Boorman, “Map making: Constructing, combining, and inferring on abstract cognitive maps,” *Neuron*, vol. 107, no. 6, pp. 1226–1238.e8, 2020, <https://doi.org/10.1016/j.neuron.2020.06.030>

- [15] A. B. Levina, P. G. Chernenko, and S. V. Boyko, "Binary code compression based on decision trees," in *Communications in Computer and Information Science*, vol. 2603. Cham, Switzerland: Springer, 2026, pp. 155-167, https://doi.org/10.1007/978-3-032-04758-8_12
- [16] L. Sun, M. A. Rodriguez, and P. Kumar, "Teaching Huffman coding through interactive binary tree visualizations: An educational framework," *Computer Science Education*, vol. 35, no. 1, pp. 45-67, 2025
- [17] R. E. Mayer and L. Fiorella, Eds., *The Cambridge Handbook of Multimedia Learning*, 2nd ed. Cambridge, U.K.: Cambridge University Press, 2022 <https://doi.org/10.1017/9781108894333>
- [18] G. Yildiz, C. O. Güzeller, and Z. Özmen, "The effect of multisensory instructional approach on the academic achievement and retention of students," *Journal of Education and Practice*, vol. 11, no. 9, pp. 148-159, 2020
- [19] E. Doğan, B. Yıldız, and Ö. Kızılkaya, "Visualizing algorithms to enhance understanding in data structures," *International Journal of Computer Science Education*, vol. 11, no. 2, pp. 45-56, 2022.
- [20] H. Lee, S. Kim, and J. Park, "Graphical programming for algorithm education," *Computers & Education*, vol. 165, p. 104151, 2021 <https://doi.org/10.1016/j.compedu.2021.104151>
- [21] R. Gómez-Pablos, M. del Pozo, and A. Muñoz-Repiso, "Using digital resources for active learning in computer science," *Education and Information Technologies*, vol. 25, no. 3, pp. 2113-2133, 2020
- [22] M. T. Goodrich, R. Tamassia, and M. H. Goldwasser, *Data Structures and Algorithms in Python*, 2nd ed. Hoboken, NJ, USA: Wiley, 2022.
- [23] A. Goujon, J.-F. Héroul, and N. Grimault, "Complex procedural knowledge in computing: An analytical framework for studying learning in programming," *Revue Française de Pédagogie*, no. 212, pp. 53-72, 2021
- [24] E. R. Hilgard, *Personality and Hypnosis: A Study of Imaginative Involvement*. Chicago, IL, USA: University of Chicago Press, 1979
- [25] B. Kaufman, C. G. DeYoung, J. R. Gray, L. Jiménez, J. Brown, and N. Mackintosh, "Implicit learning as an ability," *Cognition*, vol. 116, no. 3, pp. 321-340, 2010 <https://doi.org/10.1016/j.cognition.2010.05.011>

