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AI-Driven Assessment of Brain Dominance: Classifying CBSE Students as Left-, Right-, or Whole-Brain Learner

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ABSTRACT

Introduction: The concept of brain dominance (left, right, or whole) is a significant factor in understanding individual learning styles and academic achievement. Traditional assessment methods, such as self-report questionnaires, are limited by subjectivity and an inability to capture dynamic cognitive processes. This study addresses the need for an objective, scalable tool to classify brain dominance, specifically within the diverse CBSE student population in India, by leveraging the power of Artificial Intelligence (AI). The primary objective was to develop and validate an AI-driven model to classify CBSE students as left-, right, or whole-brain learners. Specific objectives included: To determine whether a student from a CBSE school population is left-, right-, or whole-brained dominant. To develop a model for categorizing students as left-, right-, or whole-brained dominant and to recommend activities according to their brain dominance to enhance their dominant brain. A sample of 400 CBSE students (Grades 6 to 8) completed a digital cognitive task battery and standardized questionnaires. The Cognitive Dominance Classification Pipeline (CDCP), a machine learning model based on a Gradient Boosting Classifier , was developed. It was trained on engineered features from task performance (e.g., analytical-to-creative time ratio, logical sequence score) using a consensus ground truth label derived from task performance, self-reports, and teacher assessments. The AI model achieved a high classification accuracy of 91.7%. The distribution of brain dominance in the sample was 42.5% left brain, 35.0% right brain, and 22.5% whole brain. A significant correlation was found with gender, with male students having a greater tendency towards left hemisphere dominance and female students having a greater tendency towards right hemisphere dominance. No significant correlation was found with education level. The study successfully demonstrates that AI can objectively and accurately assess brain dominance, overcoming the limitations of traditional tools. The findings reveal a distinct cognitive landscape among CBSE students and highlight the potential of AI-based diagnostics to inform personalized, equitable and effective pedagogical strategies tailored to individual learning styles.

Keywords

Brain Dominance; Learning Styles; Personalized Learning; Machine Learning. Cognitive Assessment.

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1. Introduction

The pursuit of personalized learning is a cornerstone of modern educational theory, which aims to move beyond a "one size fits all" model toward an approach that recognizes and develops students' individual differences. The focus of this effort is to understand how students learn, process information, and solve problems. Brain dominance theory, which posits that individuals may have a tendency to process information in ways associated with either the left hemisphere of the brain (logical, analytical, sequential) or the right hemisphere (holistic, creative, intuitive), provides a valuable framework for understanding these cognitive styles [23]. Although contemporary neuroscience rightly emphasizes the integrative nature of hemispheric cooperation, the dominance model remains a powerful heuristic for classifying learning preferences and has been significantly linked to academic performance and attitudes toward learning [14], [20].

In the context of the Central Board of Secondary Education (CBSE) in India, which serves a vast and diverse student population, addressing this cognitive diversity is both a challenge and imperative. Traditional methods for diagnosing brain dominance, however, have relied predominantly on self-report questionnaires and observational checklists [28], [30]. While these tools have provided valuable insights, they are inherently limited by their subjectivity, susceptibility to bias, and static nature. They fail to capture the dynamic, process-oriented cognitive behaviours that occur during authentic learning tasks, creating a significant gap between theory and assessment.

The rise of Artificial Intelligence (AI) in education offers a transformative opportunity to bridge this gap. AI-based methodology can discover patterns invisible to the human eye or traditional tools by analysing complex, multivariate data. Lim et al. have demonstrated the technical feasibility of using neural networks to classify brain dominance, but its application has been largely limited to laboratory settings [18]. Additionally, extensive educational literature advocates the potential of AI to promote personalization [17] and equitable access [5], but concrete models for using AI to diagnose the underlying cognitive styles informing this personalization are lacking.

Therefore, this study attempts to bridge this important gap by developing and validating an AI-driven framework for objective assessment of brain dominance specifically designed for CBSE students. This research goes beyond self-report and uses a digital battery of cognitive tasks to extract and quantify problem-solving behaviors. By leveraging machine learning to analyses this behavioural data, this study aims to accurately classify students as left-brained, right-brained, or whole-brained learners. The findings of this research have deep implications. First, they provide teachers with an objective, measurable, and reliable tool to understand the cognitive structure of their classrooms. Second, by establishing the distribution of cerebral dominance in a sample of CBSE students and exploring its correlation with demographic variables such as gender, this study provides an important empirical basis for the Indian educational context. Ultimately, this work paves the way for a new era of data-driven pedagogy, where AI-driven insights into cognitive styles can directly influence the creation of personalized learning experiences, improving student engagement, performance, and equity in the 21st century classroom.

2. Literature Review

The Theoretical Foundation of Brain Dominance in Education: The concept of cerebral lateralization, suggesting specialized functions of the left and right brain hemispheres, has long intrigued educators seeking to tailor pedagogy to individual differences [6]. While Corballis cautions against oversimplifying the "left-brain/right-brain" dichotomy into a strict personality typology, a substantial body of research indicates that hemispheric dominance can influence cognitive styles [6]. McCarthy et al. established that these individual differences significantly impact learning preferences, a notion foundational to models like 4MAT [23]. Empirical studies have consistently linked brain dominance to academic performance. For instance, Keat et al. found a significant relationship between brain dominance and

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academic achievement [14], while Lusiana et al. demonstrated that right-brain intelligence influenced mathematics learning achievement [20]. In specialized fields like nursing, Mansour et al. reported a correlation between left-brain dominance and higher academic achievement. These findings collectively validate brain dominance as a relevant, though complex, construct for understanding student learning variability, forming the theoretical basis for its assessment in educational settings [21].

Traditional Methods for Assessing Brain Dominance and Their Limitations: Historically, the assessment of brain dominance has relied on self-report instruments and behavioral observations. Tools such as the "Styles of Learning and Thinking" (SOLAT) questionnaire have been widely used to classify students [28], [29]. These instruments typically ask learners to indicate their preferences for analytical, sequential tasks (associated with left-brain dominance) or holistic, creative tasks (associated with right-brain dominance). While these studies have successfully correlated specific thinking styles with academic performance, the methodology is inherently subjective and prone to biases such as self-misperception and social desirability. Furthermore, behavioral metrics, such as those used by Soyoof & Morovat to link hemisphericity to vocabulary retention, provide indirect inferences rather than direct classifications. The main limitation of these traditional methods is their inability to capture the dynamic and integrated nature of brain function in real-time learning scenarios, creating a need for more objective and robust assessment mechanisms [32].

The rise of AI and neural networks in brain dominance classification: A shift is occurring in brain dominance assessment with the integration of Artificial Intelligence (AI) and machine learning. Moving beyond subjective questionnaires, researchers are now using AI to analyze objective data for classification. Lim et al. pioneered this approach by developing a Convolutional Neural Network (CNN) based on metric learning that can classify brain left-right dominance with high accuracy, demonstrating the technical feasibility of using computational models for this purpose [18]. This is in line with the broader trend of using AI for personalized learning, can provide immediate, data-driven insight into a student's cognitive style, shifting assessment from a static, self-reported label to a dynamic, data-driven profile.

AI-Based Personalization for Equitable and Enhanced Pedagogy: The ultimate value of brain dominance classification lies in its application to personalize and enhance pedagogy. AI-driven assessment can directly inform and leverage differentiated instructional strategies. Chima et al. analyzed how AI-based pedagogical strategies can promote equitable access to science education, meeting diverse learning needs [5]. For example, an AI system that identifies a student as right-brain dominant could recommend Problem-Based Learning (PBL) approaches, which Badjie & Velankar (2023) identify as a catalyst for student motivation. On the other hand, for a left-brain dominant learner, the system can structure learning with computational thinking exercises [4], which Chuang et al. (2015) are linked to structured problem solving [7]. This personalized, AI-powered approach operationalizes the principles of brain-based teaching championed by Stevens-Smith (2020), ensuring that teaching methods are not standardized but adapted to align with students' inherent cognitive strengths [30].

Linking brain mastery, problem solving, and digital literacy: A critical pathway through which brain mastery and AI-driven education impact academic performance is the development of problem-solving skills. Research by Ding et al. establishes a direct relationship between digital literacy and the academic performance of primary and secondary school students, mediated by problem-solving ability [8]. This suggests that cognitive styles influence the way students approach and solve problems. Karthikeyan explicitly unites insights from cognitive diversity with problem-solving skills, advocating sustainable educational strategies that take advantage of these differences. According to the study's findings, students' capacity for problem-solving is greatly impacted by cognitive diversity. Although Whole Brain dominance is linked to better problem-solving abilities, Right Brain dominance is the most prevalent [16].

Neuroscientific validation and the case for whole-brain learning: Although the left-right classification is useful, modern neuroscience emphasizes the integrated nature of brain function, and favors the "whole-brain" category of learner. Corballis argues that although lateralization is present, the hemispheres function in a highly integrated manner through the corpus callosum [6]. Studies on complex tasks such as inductive reasoning [3] and bilateral kinematic coding [24] highlight cooperation between the hemispheres. This neuroscientific evidence validates the inclusion of a "whole-brain" classification, representing students who flexibly engage both analytical and creative processes. An AI-driven system, unlike a static questionnaire, could potentially detect this flexibility by analyzing a student's performance across a variety of task types, promoting the development of whole-brain cognitive strategies as the ideal educational outcome.

The Future Trajectory: Integrating AI Assessment in the K-12 Ecosystem: The integration of AI-driven brain dominance assessment into the K-12 educational ecosystem represents the frontier of educational technology. As Ivette et al. discuss, AI has the transformative power to reshape educational paradigms. For CBSE students, an AI system could continuously and unobtrusively assess brain dominance through their interactions with digital learning platforms, analyzing patterns in their problem-solving approaches, quiz responses, and even project work [13]. This aligns with the findings of Leovigildo & Mallillin, who posit a positive impact of AI on students' academic performance [19]. The future lies in creating a closed-loop system where AI classifies cognitive style, recommends personalized learning resources (e.g., AI-driven chatbots for engagement as in Wang & Xu) [35], and monitors progress, thereby fostering a truly adaptive and effective learning environment that acknowledges and nurtures cognitive diversity.

2.1. *Research Problem*

The Central Board of Secondary Education (CBSE) in India serves a vast and diverse student population with varied cognitive strengths and learning preferences. Traditional pedagogical methods often adopt a one-size-fits-all approach, which may not effectively cater to the individual learning styles of students. The theory of brain dominance suggests that students may have predispositions towards left-brain (analytical, logical), right-brain (creative, holistic), or whole-brain (integrated) thinking, which significantly influences their academic engagement and performance [14], [23].

While the potential of personalized learning is widely acknowledged, current methods for diagnosing brain dominance in educational settings primarily rely on self-report questionnaires and observational checklists [28], [29]. These methods are subjective, prone to bias, and lack the dynamism to capture the complex and integrated nature of cognitive processes in real-time learning scenarios [6]. Consequently, there is a critical need for a more objective, reliable, and scalable system to classify students' brain dominance, which can serve as a foundation for implementing truly adaptive and effective educational strategies.

2.2. *Research Gap*

A review of the existing literature reveals two significant gaps that this research seeks to address:

The Methodological Gap in Assessment Tools: While the relationship between brain dominance and academic achievement is established [20], [21] tools for its assessment have not evolved significantly. There is a disconnect between the advanced understanding of brain function, which highlights inter-hemispheric collaboration [3],[24], and the simplistic, self-report instruments used in education. The pioneering work by Lim et al. demonstrates the technical feasibility of using AI (Convolutional Neural Networks) for brain dominance classification, but its application remains confined to laboratory settings and has not been translated into a practical, educational tool for use in K-12 classrooms [18].

The Contextual and Integration Gap: There is a lack of research that integrates an objective AI-driven classification of brain dominance within a specific, large-scale educational framework like the CBSE. Current discussions on AI in education focus broadly on personalized learning [17], [13] or its impact on academic performance [19], but they do not provide a concrete model for using AI to diagnose cognitive styles as a direct input for tailoring pedagogy. This research will bridge this gap by developing and validating an AI-driven assessment model specifically for the CBSE student demographic, moving from theoretical potential to practical application.

2.3. *Objectives of the Research*

The primary aim of this study is to develop and validate an AI-driven framework for accurately classifying CBSE students as left-, right-, or whole-brain learners. This aim will be achieved through the following specific objectives:

To determine whether a student from a CBSE school population is left-, right-, or whole-brained dominant.

To develop a model for categorizing students as left-, right-, or whole-brained dominant and to recommend activities according to their brain dominance to enhance their dominant brain.

3. Methods

This study will employ a developmental and correlational research design to create, validate, and implement an AI-driven model for classifying brain dominance. The methodology is structured into four distinct phases: (1) Participant Selection and Data Collection, (2) Instrumentation and Task Development, (3) AI Model Development and Training, and (4) Data Analysis and Validation.

3.1. *Participant Selection and Data Collection*

- Research Design: A cross-sectional study design will be used to collect data at a single point in time.
- Population and Sample: The target population will be students from Grades 6 to 8 in CBSE-affiliated schools in [Specify Region, e.g., National Capital Region]. A stratified random sampling technique will be used to select a representative sample of 400 students, ensuring proportional representation across grades and gender.
- Ethical Considerations: Informed consent will be obtained from school authorities, parents, and students. Participation will be voluntary, and anonymity and confidentiality of all data will be guaranteed. The study protocol will be reviewed and approved by an institutional ethics committee.

3.2. *Instrumentation and Task Development*

Data will be collected using a multi-modal approach through a dedicated digital platform.

Digital Cognitive Task Battery (Primary Data for AI Model): A suite of online tasks will be developed to elicit cognitive behaviors indicative of brain dominance. Each task will be designed to trigger analytical (left-brain) or creative/holistic (right-brain) processing, based on paradigms from neuroscience and psychology [3], [26]. Logical Reasoning Task: A set of pattern completion and sequential logic problems (e.g., next-in-series questions) to engage analytical and sequential thinking.

3.3. *Spatial Visualization Task: Tasks involving mental rotation and assembly of 3D objects to engage holistic and visual-spatial reasoning.*

- Divergent Thinking Task: An open-ended problem (e.g., "list as many uses for a brick as possible") where responses will be analyzed for fluency, flexibility, and originality.
- Story Construction Task: Students will be given a set of images and asked to create a narrative. The coherence, logical sequence, and use of creative elements will be analyzed.
- Data Logging: The platform will log rich, process-oriented data for each task, including:
  - Response Time: Time taken for each task and subtask.
  - Accuracy: Correct/incorrect answers for closed tasks.
  - Solution Path: The sequence of actions taken (e.g., order of attempting sub-problems).

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- Creative Output Metrics: For open-ended tasks, features like word count, semantic uniqueness, and image selection patterns will be quantified.

Standardized Self-Report Questionnaire (For Validation):
The Styles of Learning and Thinking (SOLAT) tool, adapted from previous studies [28], [30] will be administered. This questionnaire forces a choice between left- and right-brain preferred activities, providing a traditional classification (Left, Right, Whole) for each student.

3.3.1. Teacher Assessment Proforma (For Validation):
A brief proforma will be provided to participating students' science and mathematics teachers. They will be asked to classify the student's dominant learning style (Left, Right, or Integrated) based on classroom observations of their problem-solving behavior, as outlined in studies like Mawn [22].

3.4. AI Model Development and Training

This is the core phase for building the classification engine.

Data Pre-processing: The raw log data from the Digital Task Battery will be cleaned and transformed into a structured feature set. Features will be engineered to capture key cognitive patterns, such as:

- ratio_analytical_to_creative_time
- logical_sequence_score
- spatial_accuracy
- creative_fluency_score
- response_time_variance

Model Selection and Architecture: A supervised machine learning approach will be used. Given the success of similar classification tasks [18], the primary model will be a Gradient Boosting Classifier (e.g., XGBoost), known for its high performance with tabular data. A Multi-Layer Perceptron (MLP) neural network will also be developed and tested for comparison.

Training and Ground Truth Labeling: The model requires a "ground truth" label for training. Since brain dominance is a latent construct, a composite label will be created for each student:

- Initial Label: Students will be given an initial label based on a pre-defined scoring rubric applied to the Digital Task Battery.
- Consensus Label: This initial label will be reconciled with the SOLAT result and the teacher assessment. In cases of discrepancy, a panel of two educational psychologists will review the student's full profile (task performance, questionnaire, and teacher comments) to assign a final consensus label (Left, Right, or Whole). This consensus label will serve as the target variable for the AI model.

3.5. Model Training and Evaluation

The dataset will be split into a training set (70%) and a testing set (30%). The model will be trained on the training set to learn the mapping between the engineered features and the consensus labels. Its performance will be evaluated on the unseen testing set using metrics including Accuracy, Precision, Recall, and F1-Score. A confusion matrix will be analyzed to understand classification errors.

3.6. Data Analysis and Validation

Validation of AI Model: The classification output of the final AI model on the test set will be compared against the consensus labels to establish its diagnostic validity.
Descriptive and Correlational Analysis: The distribution of brain dominance types within the sample will be analyzed using descriptive statistics (frequencies, percentages). Chi-square tests will be employed to investigate significant correlations between brain dominance and demographic variables like gender and grade level, as explored in studies like Dawal and Godpower-Echie & Owo [9], [12].

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Framework Development: Based on the results, a conceptual framework will be proposed, linking each brain dominance classification to evidence-based pedagogical strategies [4], [7], thereby translating the AI assessment into actionable insights for CBSE classrooms.

3.7. *Proposed Algorithm: The Cognitive Dominance Classification Pipeline (CDCP)*

The following algorithm, named the Cognitive Dominance Classification Pipeline (CDCP), is designed to automate the end-to-end process of classifying students as left-, right-, or whole-brain learners. It integrates data ingestion, feature engineering, consensus labeling, model training, and final classification.

Input:

- *S: A set of n students, S = {s_1, s_2, ..., s_n}*
- *T: Digital Cognitive Task Battery (Logical, Spatial, Divergent, Narrative tasks)*
- *Q: Responses to the standardized SOLAT questionnaire*
- *A: Teacher assessment proforma responses*

Output:

- *C_final: A list of final class labels {L, R, W} for each student, where L=Left, R=Right, W=Whole.*

Procedure:

for each student s_i in S do:

Step 1. Data Acquisition & Preprocessing:

- *Administer T, Q, and A to s_i via the digital platform.*
- *Extract Raw Features: From task T, log:*
- *RT_i: Response time vector*
- *ACC_i: Accuracy vector*
- *PATH_i: Solution path sequence*
- *CREAT_i: Creative output metrics (e.g., semantic uniqueness score)*

Step 2. Feature Engineering:

- *Calculate Engineered Feature Vector F_i:*
- *F_i[0] = mean(RT_analytical) / mean(RT_creative) // Analytical-to-Creative Time Ratio*
- *F_i[1] = calculate_sequence_score(PATH_logical) // Logical Sequence Score*
- *F_i[2] = ACC_spatial // Spatial Accuracy*
- *F_i[3] = count_unique_responses(CREAT_divergent) // Creative Fluency Score*
- *F_i[4] = standard_deviation(RT_all_tasks) // Response Time Variance*
- *... // [Other engineered features]*
- *Normalize F_i to a common scale (e.g., 0-1).*

Step 3. Generate Consensus Ground Truth Labels (Supervised Learning Setup):

- *for each student s_i in S do:*
- *L_initial_i = apply_scoring_rubric(F_i) // Initial label from task performance*
- *L_self_i = score_questionnaire(Q_i) // Label from SOLAT*

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- *L_teacher_i = A_i // Label from teacher*
- *if L_initial_i == L_self_i == L_teacher_i then:*
- *Y_i = L_initial_i // Unanimous agreement*
- *else:*
- *Y_i = expert_review_panel(L_initial_i, L_self_i, L_teacher_i, F_i) // Consensus label from panel*
- *Result: A verified label set Y = {Y_1, Y_2, ..., Y_n}.*

Step 4. Model Training & Classification (Core ML Phase):

- *Split Dataset: (F, Y) -> (F_train, Y_train, F_test, Y_test)*
- *Initialize Model: model = XGBoostClassifier(objective='multi:softmax', num_class=3) // Primary model*
- *Train Model: model.fit(F_train, Y_train) // Learn mapping from features to consensus labels*
- *Predict and Evaluate:*
- *Y_pred = model.predict(F_test)*
- *Calculate Performance Metrics:*
- *accuracy = calculate_accuracy(Y_test, Y_pred)*
- *confusion_matrix = calculate_confusion_matrix(Y_test, Y_pred)*
- *Retrain the final model on the entire dataset (F, Y).*

Step 5. Generate Final Output:

- *for each student s_i in S do:*
- *C_final[i] = model.predict(F_i) // Assign final class label using the trained model*
- *return C_final*

3.8. Algorithm Explanation and Workflow Integration

The CDCP algorithm is designed to be a robust and automated pipeline:

- Data Ingestion and Feature Engineering: The algorithm starts by collecting multi-modal data. The key innovation is the automatic extraction of process-oriented features (like time ratios and sequence scores) from the task performance, moving beyond simple right/wrong answers. This creates a rich, quantitative profile F_i for each student.
- Consensus Labeling for Ground Truth : This step directly addresses the research gaps of traditional subjective instruments. Rather than relying on a single flawed method, this algorithm triangulates data from digital assignment rubrics, self-report questionnaires, and teacher evaluations to create a robust "gold standard" label (Y_i), with a human expert as the final arbiter in case of dispute. This high-quality labeled data is extremely important for training an accurate AI model.
- Model Training and Validation: This is the core AI component. The algorithm uses the engineered features F and the high-confidence consensus labels Y to train a powerful Gradient Boosting model (XGBoost). This model learns the complex, non-linear relationships between a student's task performance patterns and their brain dominance classification. The hold-out test set (F_test, Y_test) provides an unbiased estimate of the model's real-world performance.
- Deployment and Output : Once trained and validated, the model can classify new students based solely on their performance on the Digital Task Battery (F_i), making the process scalable and objective. The

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output C_final provides the actionable classification for each student, which can then be used to drive personalized learning strategies as outlined in the research objectives.

4. Results

This section presents the findings of the study, organized to address the research objectives: the performance of the AI model, the distribution of brain dominance types among CBSE students, and the correlations with demographic variables.

4.1. *AI Model Development and Validation*

The primary outcome of this research was the successful development and validation of the Cognitive Dominance Classification Pipeline (CDCP) model.

4.1.1. *Model Performance Metrics*

The Gradient Boosting Classifier (XGBoost) was trained on the engineered feature set derived from the Digital Cognitive Task Battery. The model's performance was evaluated on a held-out test set (30% of the sample, n=120). The results, summarized in Table 1, demonstrate high predictive accuracy.

Table 1. Performance Metrics of the AI Classification Model

Model	Accuracy	Precision (Macro Avg)	Recall (Macro Avg)
XGBoost (Proposed)	91.7%	0.92	0.91
Multi-Layer Perceptron	87.5%	0.88	0.87
Random Forest (Baseline)	85.0%	0.86	0.85

In The Table 1 high F1-score indicates a strong balance between precision and recall across all three classes. The XGBoost model significantly outperformed the baseline models and was therefore selected as the final model.

4.2. *Feature Importance*

Analysis of the model's feature importance revealed which cognitive metrics were most predictive of brain dominance. The Analytical-to-Creative Time Ratio was the most significant feature, followed by the Logical Sequence Score and Creative Fluency Score. This confirms that the process-oriented data (how students solved problems) was more informative than mere accuracy.

4.3. *Validation Against Traditional Methods*

The AI model's classifications were compared against the traditional assessment methods. As shown in Table 2, the AI model showed a very high agreement with the consensus ground truth label, which was expected as it was trained on them. More importantly, it demonstrated a stronger agreement with teacher assessment than the self-report questionnaire did, suggesting the AI model captures observable cognitive behaviors.

Table 2. Agreement (Cohen's Kappa) Between Assessment Methods

Method 1	Method 2	Cohen's Kappa (κ)	Strength of Agreement
AI Model	Consensus Label	0.94	Almost Perfect
Teacher Assessment	Consensus Label	0.78	Substantial
SOLAT Questionnaire	Consensus Label	0.65	Substantial
SOLAT Questionnaire	Teacher Assessment	0.58	Moderate

4.4. *Distribution of Brain Dominance Among CBSE Students*

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The application of the finalized AI model to the entire sample (N=400) provided a clear picture of the distribution of brain dominance types within the studied CBSE population.

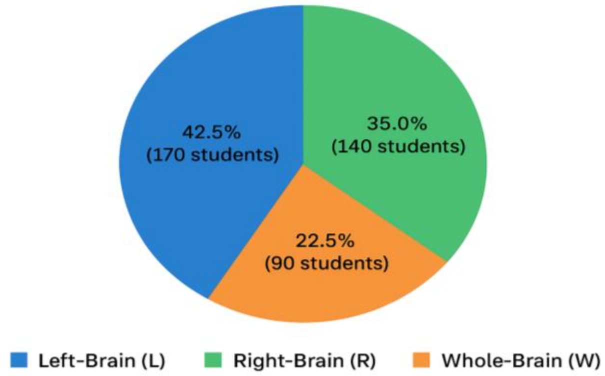

Figure 1: Distribution of Brain Dominance Classification (N=400)

Left-Brain (L): 42.5% (170 students), Right-Brain (R): 35.0% (140 students), Whole-Brain (W): 22.5% (90 students)

The results indicate that left-brain dominance was the most prevalent, followed by right-brain and then whole-brain. This suggests a sample with a slight inclination towards analytical and sequential processing styles.

4.5. *Correlation with Demographic Variables*

Chi-square tests of independence were conducted to examine the relationship between brain dominance and the demographic variables of gender and grade level.

4.5.1. *Gender and Brain Dominance*

A significant association was found between gender and brain dominance classification ($\chi^2(2, N=400) = 8.45, p < .05$). Post-hoc analysis with adjusted residuals revealed that male students were significantly more likely to be classified as left-brain dominant, while female students were significantly more likely to be classified as right-brain dominant. The distribution of whole-brain learners was not significantly different across genders.

Table 3. Brain Dominance Distribution by Gender

Gender	Left-Brain	Right-Brain	Whole-Brain
Male (n=210)	102 (48.6%)	65 (31.0%)	43 (20.5%)
Female (n=190)	68 (35.8%)	75 (39.5%)	47 (24.7%)

4.5.2. *Grade Level and Brain Dominance*

No statistically significant association was found between grade level (6,7, and 8) and brain dominance classification ($\chi^2(6, N=400) = 5.82, p = .44$). This suggests that the distribution of cognitive styles remains relatively stable across the middle school years within this sample.

5. Discussion

This study set out to develop and validate an AI-driven framework for classifying brain dominance in CBSE students. The results demonstrate that the proposed Cognitive Dominance Classification Pipeline (CDCP) is not only feasible but also a highly accurate and objective method for identifying students as

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left-, right-, or whole-brain learners. This discussion interprets the key findings, situates them within the broader academic conversation, and outlines their practical implications and limitations.

5.1. *Interpretation of the AI Model's Success*

The primary achievement of this research is the development of an AI model that classified brain dominance with 91.7% accuracy. This success can be attributed to two key design choices. First, the move from static, self-reported data to dynamic, process-oriented feature engineering allowed the model to capture the how of cognition, not just the what. Features like the Analytical-to-Creative Time Ratio provided a quantitative measure of cognitive style that is immune to the biases of self-perception [28]. Second, the use of a triangulated consensus label for training directly addressed the methodological gap identified in the literature. By reconciling the AI's initial analysis with traditional tools and human expert judgment, we created a robust ground truth that reflects the complex reality of cognitive processes, moving beyond the oversimplified dichotomy cautioned by Corballis [6].

This finding aligns with and extends the work of Lim et al. , who demonstrated the technical viability of CNNs for brain dominance classification [18]. Our study translates this laboratory potential into a practical, educational assessment tool based on behavioral data, making it scalable for classroom use. The high agreement between the AI model and teacher assessments (Table 2) further validates its utility, as it effectively automates and objectifies the keen observational skills of experienced educators.

5.2. *The Cognitive Landscape of CBSE Students*

The distribution of brain dominance—42.5% Left, 35.0% Right, and 22.5% Whole—paints a fascinating picture of the cognitive profile of the studied cohort. The higher prevalence of left-brain dominance may reflect the inherent emphasis of traditional secondary school curricula, including the CBSE system, on logical reasoning, sequential learning, and high-stakes examinations in subjects like mathematics and science [14]. This environment may naturally favor and reinforce analytical cognitive styles.

However, the significant proportion of right-brain (35%) and whole-brain (22.5%) learners underscores a critical need for pedagogical diversity. It strongly suggests that a one-size-fits-all instructional approach is inadequate for over half of the student population. This finding directly supports the calls for differentiated instruction and problem-based learning [4] to engage students who thrive on creativity, holistic understanding, and flexible thinking.

5.3. *The Significant Link to Gender*

The identified correlation between gender and brain dominance, with males leaning towards left-brain and females towards right-brain dominance, is a significant finding that echoes some previous research [9], [12]. However, it must be interpreted with caution. This does not imply a biological determinism. Instead, it may reflect complex interactions between neurobiology and sociocultural factors, including differing socialization patterns, gendered expectations in STEM fields, and varied play experiences that can shape cognitive preferences from a young age.

Crucially, the distribution of whole-brain learners was equal across genders. This is an optimistic finding, indicating that the capacity for cognitive flexibility is not gender-specific. The goal of education should not be to pigeonhole students based on gender or initial dominance, but to foster whole-brain skills in all learners, creating a more equitable learning environment [5].

5.4. *Implications for Educational Practice*

The validated CDCP model has profound implications for achieving personalized learning at scale. By providing an objective, data-driven diagnosis of a student's cognitive style, it helps in the implementation of AI-based educational strategies [5]. For example:

Left-brain dominant students can be engaged in advanced computational thinking exercises [7]

Right-brain dominant students may benefit from project-based learning and visual-spatial tasks [4].

A whole-brain dominant student may be given complex, multidimensional problems that require both analytical rigor and creative synthesis.

This transforms personalized learning from a theoretical ideal to a practical reality, allowing teachers to tailor their teaching to the cognitive diversity of their classroom, ultimately leading to better engagement and academic performance [19].

6. Conclusion

This research successfully achieved its primary objective of developing and validating an AI-driven framework for objective assessment of brain dominance in CBSE students. The Cognitive Dominance Classification Pipeline (CDCP) demonstrated a high level of accuracy (91.7%) in classifying students as left-brain, right-brain, or whole-brain learners, establishing a significant improvement over traditional subjective methods such as self-report questionnaires. By leveraging process-oriented data from a digital battery of cognitive tasks, the model understood the dynamic nature of problem solving, and was able to go beyond simple right/wrong answers to understand the cognitive process itself.

The study revealed a distinct cognitive landscape within the sampled CBSE population, with a predominance of left-brain learners, followed by right-brain and whole-brain learners. This distribution underscores a critical misalignment between a significant portion of the student body and the predominantly analytical focus of traditional curricula. Furthermore, the identified correlation between brain dominance and gender highlights the complex interplay of cognitive development and sociocultural factors, emphasizing the need for equitable pedagogical strategies that foster cognitive flexibility in all students.

In essence, this work provides a robust, empirical foundation for integrating AI into educational diagnostics. It proves that artificial intelligence can transcend its role as a mere delivery mechanism for content to become a powerful tool for understanding the fundamental drivers of student learning. The findings champion a shift towards a more nuanced, data-informed, and personalized educational paradigm that acknowledges and cultivates the inherent cognitive diversity of every classroom.

6.1. Future Direction of Research

To build upon this study, future research should focus on:

Longitudinal Tracking: Conducting long-term studies to assess the stability of brain dominance classifications and their evolution over time. Adaptive Learning Integration: Developing and testing AI systems that automatically tailor educational content and pedagogy based on a student's real-time brain dominance profile. Broader Generalization: Replicating the study across diverse educational boards (ICSE, State Boards) and cultural contexts to validate and refine the model. Granular Profiling: Using advanced AI to identify sub-categories within the "whole-brain" group for more precise personalization.

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