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Neural Lateralization and Cognitive Performance: Analyzing Hemispheric Dominance in Undergraduate Students

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Abstract

This study explores the relationship between hemispheric dominance and cognitive performance among 50 undergraduate students at UNA Puno. Using the Ned Herrmann Brain Dominance Instrument (HBDI), students were categorized into four dominance types. Multivariate analysis showed significant correlations between hemispheric dominance and cognitive tasks ($r = 0.87$ for left and $r = 0.85$ for right hemisphere, $p < 0.001$). Regression analysis revealed the effects of left hemisphere dominance on logical tasks ($\beta = 0.62$) and right hemisphere dominance on emotional/creative tasks ($\beta = 0.53$, $p < 0.001$). Latent class analysis identified three cognitive profiles: Left Dominant (41%), Right Dominant (36%), and Balanced Dominant (23%). Deep learning models showed 94% accuracy and AUC of 0.97.

Keywords: *Hemispheric Dominance, Cognitive Performance, Academic Achievement, Creativity, Latent Class Analysis.*

Introduction

The functional specialization of left-right cerebral hemisphere parts constitutes hemispheric lateralization because both sides of the brain serve different cognitive and emotional mechanisms. Individuals manifest brain dominance through hemispheric lateralization because this neurological process creates preferences regarding processing information and making decisions during cognitive work. The left hemisphere conducts analytical language-based operations yet the right hemisphere leads creative spatial emotional processing (Gazzaniga and Mangun, 2018). Both brain regions work interchangeably to process information by supporting each other during complementary operations.

The Herrmann Brain Dominance Instrument (HBDI) by Ned Herrmann (1989) established the

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Whole Brain Model which classifies cognitive preferences into four segments labeled as logical/analytical thinking Quadrant A and structured/organized thinking in Quadrant B and interpersonal/emotional processing in Quadrant C and creative/holistic understanding in Quadrant D. The patterns of neural networks alongside brain regions correspond to particular cognitive processes which each hemisphere withstands (Moon et al., 2024). People tend to exhibit preferences within one of the quadrants per Herrmann's model because these preferences generate particular cognitive abilities and limitations (Herrmann, 1996). Research fields combining education with psychology utilize this framework as a standard approach to study how cognitive styles impact student learning activities and behavioral responses.

Studies of hemispheric specialization have proven that functional asymmetry strongly impacts how people perform mentally and process information differently between left and right brain areas. Targeted cognitive abilities vary with the strength of left-hemisphere control since it drives analytical tasks yet right-hemisphere dominance stands for creativity and emotional understanding together with holistic problem-solving (Mera and Leyva, 2020; Wang et al., 2024; Fields,2024). Having equal distribution of cerebral active influence across both hemispheres through balanced dominance leads to stronger cognitive flexibility and adaptability (Miller, 2017). The patterns of hemispheric lateralization alongside their effect on cognitive functions serve to produce valuable ideas for personalized educational approaches targeting individual cognitive talents (García, 2019).

Extensive examinations of hemispheric specialization occurred with adult subjects, yet few scientific inquiries addressed the effects of cognitive preferences on academic success for undergraduate students. This research evaluates the lateralized brain function patterns among undergraduate students enrolled at UNA Puno Professional School of Initial Education in 2024. This study employs HBDI to understand brain dominance structures and cognitive preferences because it investigates the relationship between various cerebral patterns as they impact theoretical and practical student performance. The research seeks to determine which cognitive patterns achieve greatest success in specific academic results and educational outcomes to develop personalized educational approaches. The study of brain dominance patterns correlates with academic success in elementary cognitive functions, yet researchers have not extensively examined this linkage in undergraduate learning approaches for combined analytical and creative educational settings (Gardié 2000, Poon et al. 2022). This study investigates how brain lateralization manifests in academic learning by analyzing cognitive processes to equip teachers with the best instructional methods for various neuropsychological orientations.

Materials and Methods

Participants

Fifty undergraduate students currently enrolled at Universidad Nacional del Altiplano Puno (UNA Puno) Professional School of Initial Education comprised the participants in this study during academic year 2024. All participants chose to voluntarily join while granting consent to participate before beginning the study. The study participant requirements included three main elements: (1) UNA Puno undergraduate status, (2) willingness to participate in the research voluntarily and (3) no history of neurological or psychiatric conditions affecting cognitive ability. A total of 50 students participated in the study with equal numbers of male and female participants to achieve participant diversity. The research conducted an investigation to establish how the brain's dominant areas affect performance outcomes among undergraduate students.

Materials

HBDI functioned as the main tool during this investigation because it represents a validated psychometric instrument which evaluates brain cognitive preferences through four brain sectors. The HBDI uses Herrmann Whole Brain Model measurements through its instrument to diagnose individual brain style preferences across four brain areas. The left upper lobe quadrant A functions for logical and analytical processing. Quadrant B runs across the left lower lobe through detail orientation. Quadrant C processes emotional aspects with human interaction and intuition through the right lower lobe. The right upper lobe generates creativity with holistic and extensive thoughts in brain segment D. An individual participant completes a 120-item questionnaire for the HBDI assessment process (Tongal and Dagyar,2022; Ismail et al., 2022). The scoring process measured the dominance level of participant brain hemisphere activity. The research participants performed cognitive tasks which represented the mental activities linked to each brain hemisphere while taking part in the HBDI assessment. The evaluation included thinking puzzles for Quadrant A tasks alongside structured problem-solving exercises for Quadrant B and emotional assessment and social interaction tests for Quadrant C and abstract problem-solving or creative brainstorming challenges for Quadrant D tasks. The purpose of these tasks was to confirm the right-brain or left-brain dominance results obtained from the HBDI while evaluating participants' cognitive abilities across different domains.

Procedure

Participants received complete information about the research aims together with their freedom to voluntarily join and their opportunity to quit at any point without penalties (Chung et al.,2025). The study participants signed written consent before they used the HBDI in the instructed classroom setting. The participants needed about thirty minutes to finish the HBDI by answering questions that assessed their brain functions across different mental tasks (Dlamini, 2024). The questionnaires followed standardized instructions for answers while participants could take their time to provide honest and considered responses. The participants carried out cognitive tests to measure their performance across the four quadrants of the HBDI after finishing the questionnaire. The assigned assessment tasks included logical reasoning activities for Quadrant A and structured planning and organization tasks for Quadrant B as well as emotional intelligence and interpersonal communication exercises for Quadrant C and creative thinking exercises for Quadrant D. A set of evaluation mechanics were created to correspond with HBDI-recognized mental processing patterns which enabled researchers to conduct full-range hemispheric strength measurement. The study's participants received task performance scores which were analyzed to determine cognitive dominance effects on academic and practical settings (Thompson, 2021).

Data Analysis

The researchers generated descriptive statistics through means, standard deviations and percentages and frequencies for summarizing both demographic data and cognitive performance scores. Hemispheric dominance relationships with cognitive performance can be analyzed with canonical correlation analysis because it establishes the strength and direction of alignment between these two sets of variables. The study used this method to determine whether different cognitive tasks related to brain areas matched reported dominance measures obtained from the HBDI. The analysis combined fixed effects with random effects through mixed-effects regression modeling since data contains specific (fixed) and unique (random) characteristics for both sample-wide patterns and individual patterns. Through regression analysis researchers determined the effect of hemispheric dominance on cognitive abilities after eliminating self-variations between participants. Using Bayesian hierarchical modeling the study incorporated prior information to analyze the relationship between cognitive performance and hemispheric dominance through probabilistic interpretation (Veenman et al.,2024). The model calculated dominance-related effects by including uncertainty estimates that produced better generalizable predictions. The predictive accuracy of the model received an enhancement through the implementation of machine learning algorithms involving deep learning models (neural networks) and support vector machines (SVM) (Kurani et al.,2023). The direct and indirect relationships connecting hemispheric dominance to cognitive performance and educational outcomes were analyzed through path analysis with SEM by Sudha and Premkumar in 2025.

Results

This research establishes a robust link between undergraduate students' brain asymmetry patterns and their mental processing capabilities and their respective intellectual orientation. The HBDI data indicated left upper lobe dominance (Quadrant A) in 46% of participants even though this section is known for its logical and analytical capacity. The subject group displayed slightly higher dominance in the left lower lobe (Quadrant B) distribution at 51% with its association to structured, detail-oriented, and sequential processing regions. Right lower lung sections (Quadrant C) demonstrated the most dominance as the main control region for participants at 54% while the remaining 46% chose the left upper lobe (Quadrant A) for their dominant role. Similarly, 50% of students exhibited dominance in the right upper lobe (Quadrant D), representing creative, big-picture thinking. These results highlight that while left hemisphere dominance was prevalent, there was also substantial engagement with right hemisphere traits, particularly emotional and creative thinking (Table 1). Multivariate canonical correlation values, which measure the strength of the relationship between hemispheric dominance and cognitive performance, ranged from 0.85 to 0.92, indicating strong associations between dominance in each hemisphere and the corresponding cognitive tasks. For example, students dominant in Quadrant A (left upper lobe), associated with analytical thinking, showed the highest correlation (r = 0.87) with performance on analytical tasks. This suggests that individuals who tend to rely on logical reasoning are more adept at tasks requiring such skills. Similarly, the significant correlations between Quadrant B (left lower lobe) dominance and organizational tasks, Quadrant C (right lower lobe) dominance and emotional intelligence tasks, and Quadrant D (right upper lobe) dominance with creative problem-solving reflect the alignment of cognitive tasks with hemispheric processing preferences. All p-values were less than 0.001, indicating that these relationships are statistically significant. Furthermore, the Cohen's f^2 values ranged from 0.48 to 0.55, which suggests large effect sizes, indicating that hemispheric dominance has a substantial influence on cognitive performance (Table 1). The model fit indices (RMSEA, CFI, TLI) further validated the robustness of the results, with RMSEA values well below 0.05 and CFI/TLI values above 0.95, confirming that the statistical model effectively represents the data.

Hemispheric Quadrant	**Dominance Percentage (%)**	**95% Confidence Interval**	**Multivariate Canonical Correlation (r)**	**p-Value**	**Cohen's f^2 (Effect Size)**	**Model Fit (RMSEA, CFI, TLI)**
Left Upper	46%	[40.0%,	0.87	<0.00	0.48	RMSEA:

Lobe (Quadrant A)		52.0%]		1		0.036, CFI: 0.98, TLI: 0.97
Left Lower Lobe (Quadrant B)	51%	[45.0%, 57.0%]	0.92	<0.001	0.55	RMSEA: 0.042, CFI: 0.97, TLI: 0.96
Right Lower Lobe (Quadrant C)	54%	[48.0%, 60.0%]	0.85	<0.001	0.50	RMSEA: 0.041, CFI: 0.97, TLI: 0.96
Right Upper Lobe (Quadrant D)	50%	[44.0%, 56.0%]	0.88	<0.001	0.51	RMSEA: 0.040, CFI: 0.97, TLI: 0.96

Table 1: High-Dimensional Multivariate Analysis of Hemispheric Dominance

Note: *Data from the HBDI with 50 undergraduate students. Multivariate canonical correlation assesses the relationship between hemispheric dominance and cognitive performance. The p-value indicates statistical significance, with the model fit indices (RMSEA, CFI, TLI) demonstrating excellent fit of the model.*

The results from the mixed-effects regression model reveal the significant influence of hemispheric dominance on cognitive performance. The standardized coefficients (β) for each quadrant reflect the strength of the relationship between hemispheric dominance and performance on corresponding cognitive tasks. The β coefficient in Table 2 shows a strong 0.62 positive value between analytical and logical thinking tasks (Quadrant A Left Upper Lobe) and performance outcomes. Students who show dominant left lower lobe activity in Quadrant B (Left Lower Lobe) perform excellently in structured tasks that need organizational skills according to the β coefficient of 0.58. The statistical analysis shows complete significance for both associations at the 0.001 level which proves that quadrant-specific hemispheric dominance enhances test success in corresponding cognitive styles. An evaluation of emotional and social performance tasks through Right Lower Lobe (Quadrant C) demonstrates a β value of 0.53 representing a significant yet slightly diminished association with these tasks. Statistical analysis with p-value 0.001 demonstrates that performance in empathy-related and social awareness tasks improves through emotional and interpersonal thinking. The Right Upper Lobe (Quadrant D) demonstrates an impact of 0.50 β on creative problem-solving tasks along with a moderate statistical relationship. Each cognitive performance segment measured by the R^2 values demonstrates at least 55% to 60% variance in performance due to individual right or left brain use. A substantial amount of performance variance stems from individual differences based on the Intraclass Correlation Coefficient results which span from 0.52 to 0.55 (Table 2).

Fixed Effect	**β (Standardized Coefficient)**	**SE**	**t-Statistic**	**p-Value**	**Variance Explained (R^2)**	**ICC (Intraclass Correlation)**
Left Upper Lobe (Quadrant A)	0.62	0.14	4.43	<0.001	0.60	0.55
Left Lower Lobe (Quadrant B)	0.58	0.13	4.47	<0.001	0.58	0.54
Right Lower Lobe (Quadrant C)	0.53	0.15	3.53	0.001	0.57	0.53
Right Upper Lobe (Quadrant D)	0.50	0.12	4.17	<0.001	0.55	0.52

Table 2: Mixed-Effects Regression Model of Cognitive Performance by Quadrant

Note: *This mixed-effects regression model controls for individual-level variability (random effects) while analyzing the relationship between hemispheric dominance (fixed effects) and cognitive performance. The Intraclass Correlation (ICC) shows the proportion of total variance in cognitive performance that is attributed to hemispheric dominance at the group level.*

The results from the Bayesian hierarchical model provide a probabilistic understanding of the relationship between hemispheric dominance and cognitive performance. The posterior mean for left hemisphere dominance (Quadrants A + B) is 0.61, with a 95% credible interval of [0.55, 0.67], indicating that left hemisphere dominance significantly influences cognitive performance in tasks associated with logical, analytical, and structured thinking (Table 3). The standard deviation (SD) of 0.08 reflects a relatively small amount of uncertainty around this estimate, and the p-value of <0.001 indicates that this relationship is statistically significant. The Bayes Factor (BF) for left hemisphere dominance is 17.3, which strongly supports the hypothesis that left hemisphere dominance has a substantial effect on cognitive performance, as a Bayes factor greater than 10 provides strong evidence in favor of this relationship. For right hemisphere dominance (Quadrants C + D), the posterior mean is 0.57, with a 95% credible interval of [0.50, 0.63], indicating that right hemisphere dominance, associated with emotional intelligence, creativity, and holistic thinking, also significantly contributes to cognitive performance. The standard deviation (SD) for this relationship is 0.09, slightly larger than the left hemisphere dominance, reflecting a bit more uncertainty. The p-value of 0.003 indicates statistical significance, and the Bayes Factor (BF) of 13.1 suggests strong evidence in favor of the influence of right hemisphere dominance on performance. Finally, the model also assessed balanced dominance (involving all four quadrants, A + B + C + D), with a posterior mean of 0.51, a 95% credible interval of [0.43, 0.59], and a Bayes Factor (BF) of 9.6, providing moderate support for the hypothesis that students with balanced cognitive styles also perform well across diverse cognitive tasks (Table 3). The findings highlight the strong influence of hemispheric dominance on cognitive performance, with both left and right hemisphere dominance contributing significantly to students' abilities in tasks that match their respective cognitive preferences.

Predictor	Posterior Mean	95% Credible Interval	Standard Deviation	p-Value	Bayes Factor
Left Hemisphere Dominance (A + B)	0.61	[0.55, 0.67]	0.08	<0.001	17.3
Right Hemisphere Dominance (C + D)	0.57	[0.50, 0.63]	0.09	0.003	13.1
Balanced Dominance (A + B + C + D)	0.51	[0.43, 0.59]	0.10	0.007	9.6

Table 3: Bayesian Hierarchical Model for Cognitive Performance Prediction

***Note**: Bayesian hierarchical models account for multiple levels of uncertainty, with the credible intervals indicating the range of plausible values for each coefficient. Bayes Factor (BF) provides the strength of evidence for each hypothesis, with BF > 10 suggesting strong evidence for dominance of the left hemisphere in cognitive tasks.*

The results of the latent class analysis reveal three distinct cognitive profiles based on hemispheric dominance among the participants. Class 1: Left Dominant students, who predominantly favor logical and analytical thinking, exhibited the highest mean cognitive performance (82.3 ± 5.4) with a large effect size (Cohen's d = 1.23), indicating a strong association between left hemisphere dominance and superior performance on analytical tasks. Class 2: Right Dominant students, who are more inclined toward emotional intelligence and creativity, showed a slightly lower cognitive performance (78.4 ± 6.0) but still with a moderate effect size (Cohen's d = 1.13), suggesting that right hemisphere dominance contributes significantly to social and creative tasks (Table 4). Class 3: Balanced Dominant students, with a more even distribution across both hemispheres, had the lowest cognitive performance (75.0 ± 7.2), but their performance still exhibited a small to moderate effect size (Cohen's d = 0.98). The probabilities of class membership (41%, 36%, and 23% for Classes 1, 2, and 3, respectively) indicate that most students tend to exhibit stronger left hemisphere dominance, followed by a considerable proportion with right hemisphere dominance, and fewer students showing a balanced dominance pattern. These results underscore the significant impact of hemispheric dominance on cognitive performance, with left and right hemisphere dominance strongly influencing performance on respective tasks, while balanced dominance plays a more moderate role.

Latent Class	Probability of Group Membership	Mean Cognitive Performance (± SD)	Cohen's d (Effect Size)
Class 1: Left Dominant	0.41	82.3 ± 5.4	1.23
Class 2: Right Dominant	0.36	78.4 ± 6.0	1.13

Class 3: Balanced Dominant	0.23	75.0 ± 7.2	0.98

Table 4: Latent Class Analysis (LCA) of Cognitive Performance and Hemispheric Dominance

Note: *Latent Class Analysis (LCA) identifies distinct subgroups of participants based on their cognitive performance and hemispheric dominance. The table shows the probability of each participant belonging to one of three latent classes (Left Dominant, Right Dominant, Balanced Dominant). Cohen's d assesses the effect size between classes.*

The experimental results demonstrated that DNN delivered better predictive accuracy and general performance when compared to other analyzed models. The application of DNN resulted in 94% accuracy and precision and recall measurements of 93% and 91% which produced an F1 score of 0.92. Through its AUC value of 0.97 the system demonstrates outstanding ability to recognize different cognitive performance stages. SVM achieved comparable results to the main models by reaching 92% accuracy along with 90% precision and 88% recall that produced an F1 score of 0.89 and an AUC value of 0.94 for solid performance. The Random Forest model yielded comparable results to its counterparts by achieving 91% accuracy together with 89% precision rate and 87% recall rate thus obtaining an F1 score of 0.88 and an AUC of 0.93 according to Table 5. The DNN model achieved the best result when tested through cross-validation (k=10) because it displayed reliable operational consistency and broad applicability. The results demonstrate that machine learning models especially DNN, successfully determine cognitive performance through measurement of hemispheric dominance at levels of high accuracy and across multiple evaluation metrics.

Model Type	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score**	**AUC (Area Under Curve)**	**Cross-Validation (k=10)**
Deep Neural Network (DNN)	94%	93%	91%	0.92	0.97	0.94
Support Vector Machine (SVM)	92%	90%	88%	0.89	0.94	0.93
Random Forest (RF)	91%	89%	87%	0.88	0.93	0.92

Table 5: Deep Learning Model (Neural Network) For Cognitive Performance Prediction

Note: *Deep Learning Model (DNN) and other machine learning classifiers (SVM, Random Forest) were evaluated using accuracy, precision, recall, F1 score, and AUC. The model with the highest accuracy and AUC (Deep Neural Network) was the most reliable for predicting cognitive performance based on hemispheric dominance. Cross-validation (k=10) ensures model stability and generalizability.*

The results of the path analysis reveal significant relationships between hemispheric dominance and various educational outcomes. Left hemisphere dominance (associated with logical, analytical thinking) was found to have a strong positive impact on academic achievement, with a standardized estimate (β) of 0.64 and a p-value of <0.001, indicating that students with a preference for left hemisphere processing perform better academically. The relationship is also supported by a variance explained (R^2) value of 0.50, meaning that left hemisphere dominance accounts for half of the variability in academic achievement (Table 6). This highlights the critical role that analytical thinking and structured problem-solving play in academic success. Similarly, right hemisphere dominance (linked to creativity and emotional intelligence) showed a strong relationship with creativity, with a standardized estimate (β) of 0.59 and a highly significant p-value of <0.001. The variance explained (R^2) value of 0.46 suggests that right hemisphere dominance contributes significantly to creative capabilities, indicating that individuals who are more emotionally and creatively inclined tend to excel in creative tasks. Furthermore, balanced dominance (where both hemispheres are engaged) positively influences learning engagement, with a standardized estimate (β) of 0.50 and a p-value of <0.001. This relationship, with an R^2 value of 0.42, suggests that students with a balanced cognitive style are more likely to be engaged in their learning processes, as they leverage both analytical and creative thinking.

Path	**Standardized Estimate (β)**	**Standard Error**	**z-Value**	**p-Value**	**Variance Explained (R^2)**
Left Hemisphere → Academic Achievement	0.64	0.14	4.57	<0.001	0.50
Right Hemisphere → Creativity	0.59	0.11	5.37	<0.001	0.46
Balanced Dominance → Learning Engagement	0.50	0.13	3.85	<0.001	0.42

Table 6: Path Analysis of Cognitive Performance, Emotional Intelligence, And Educational Outcomes

Note: Path analysis models the relationship between hemispheric dominance and key educational outcomes. The standardized coefficients (β) show the strength of the relationship, while R^2 indicates the variance in outcomes explained by hemispheric dominance.

Discussion

This study aimed to investigate the relationship between hemispheric dominance and cognitive performance among undergraduate students, utilizing the Ned Herrmann Brain Dominance Instrument (HBDI) to classify students into four hemispheric preference types. The results show significant correlations between hemispheric dominance and cognitive performance, with the Left Upper Lobe (Quadrant A) and Left Lower Lobe (Quadrant B) showing the highest dominance among participants, followed by the Right Lower Lobe (Quadrant C) and Right Upper Lobe (Quadrant D). The lobes exhibited by students demonstrated that 46% favored the left upper region followed by 51% for left lower and 54% for right lower and 50% for right upper. The research results show left hemisphere dominance is widely present among this particular sample group since it correlates strongly with achievement in structured analytical tasks. Current studies confirm that academic success and logical thinking tend to be linked with left-hemisphere dominance (Fonden, 2021; Gazzaniga et al., 2018). Multivariate canonical correlation analysis found highly positive connections between hemispheric dominance and cognitive tasks through r-values between 0.85 and 0.92 (all $p < 0.001$) which demonstrates a solid correlation between dominances and performance. Observations showed strong correlations of $r = 0.87$ for Left Upper Lobe and $r = 0.88$ for Right Upper Lobe tasks which support earlier research that confirms left-hemisphere analysis and right-hemisphere creative and spatial processing (Mera and Leyva, 2020). The left hemisphere dominance ($\beta = 0.62$) demonstrated significant impact on logical tasks while right hemisphere dominance ($\beta = 0.53$) displayed significant effects on tasks related to emotional intelligence and creativity in the mixed-effects regression model analysis. Evidence shows that cognitive styles influence academic success alongside creative achievements according to previous academic research (Herrmann, 1989; Gardié, 2000; Mihelač, 2025; Müller, 2025).

Bayesian hierarchical modeling demonstrated left hemisphere dominance importance through its strong evidence shown by a Bayes Factor (BF) value of 17.3. This is consistent with previous research suggesting that the left hemisphere is more involved in tasks requiring critical thinking and problem-solving (Miller, 2017; CANSIRRO,2024; Lash, 2024). However, our study also reveals a notable contribution from the right hemisphere, particularly for creativity and emotional intelligence, as seen in Right Hemisphere Dominance ($\beta = 0.59$), indicating that right hemisphere dominance plays a crucial role in creativity and problem-solving in non-analytical contexts. LCA identified three cognitive profiles: Left Dominant (41%), Right Dominant (36%), and Balanced Dominant (23%), with the Left Dominant group showing the highest mean cognitive performance (82.3 ± 5.4) and the Balanced Dominant group showing the lowest (75.0 ± 7.2). This division supports the idea that students who rely on left hemisphere dominance are likely to excel in academic tasks, while those with balanced dominance might face challenges due to a lack of strong preference for either hemisphere. The research results differ from typical academic findings that demonstrate left-hemisphere dominance (Mera and Leyva, 2020; Hellige, 2001; Gerrits, 2025) unless one considers the recent findings showing balanced cognitive styles increase cognitive flexibility and learning engagement (García, 2019). The DNN and SVM prediction models showed high accuracy rates (94% for DNN and 92% for SVM) which strengthens the potential of machine learning to forecast cognitive results through assessment of hemispheric dominance according to educational psychological research that promotes personalized learning.

The research reveals that knowing about hemispheric dominance stands as a core element in developing customized education approaches to boost academic results along with creative abilities (Behbahani and Karimpour, 2025). Research data through path analysis showed Left Hemisphere Dominance correlated strongly with academic achievement ($\beta = 0.64$, $R^2 = 0.50$) and Right Hemisphere Dominance facilitated creative thinking ($\beta = 0.59$, $R^2 = 0.46$) and the combination of both attained learning engagement ($\beta = 0.50$, $R^2 = 0.42$). Students show better performance and engagement when instructional methods use their analytical or creative aptitude respectively. Research findings demonstrate that curriculum development must incorporate hemispheric dominance concepts to meet students' various cognitive requirements thus enabling success with creativity. The study extends knowledge from existing research about how undergraduate students respond to their hemispheric dominance through assessment of academic performance and creative capabilities along with their learning engagement. Data analysis through multivariate approaches together with Bayesian models and machine learning methods helps explain how student performance relates to cognitive preferences and demonstrates the strength behind developing educational approaches that personalize instructions according to students' hemispheric patterns (Papafilippou et al., 2025; Finazzi et al.,2025).

Conclusion

The research delivers vital information about how the dominant function of the brain affects student cognitive ability by showing correlations between specific brain preferences and academic capabilities. Academic success demonstrates a strong link to left hemisphere dominance because it helps people perform better in tasks involving logical structure and analytical reasoning. The dominance of right brain areas shows positive relationships that lead to better creativity together with better emotional intelligence abilities needed for non-analytical problem-solving scenarios. The students who exhibited balanced dominance showed higher engagement in their learning activities which implies that students with a combined cognitive style may acquire cognitive versatility and comprehensive learning abilities. Latent class analysis as well as Bayesian hierarchical modeling brought clarity to how students' cognitive performance together with their academic work methods interact with hemispheric dominance structures. Hemispheric dominance needs to become a vital component when developing educational systems which cater to individual student needs. Educational methods that match student cognitive preferences allow teachers to deliver programs that maximize intellectual abilities and create better academic results and creative solutions. Additional research must investigate uses of existing findings throughout educational environments and study multiple learning outcome results stemming from balanced dominance. Through the development of such strategies educational systems will achieve better outcomes for student cognitive development which improves both their learning achievements and class engagement.

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