Unified Report: Analysis of Cognitive Games and Academic Performance

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1 Introduction

This report consolidates findings from multiple investigations aimed at exploring the relationship between cognitive performance in brain-training games and academic achievement among fifth-grade students. The primary objective was to identify parameters that linearly predict individual behavior across different game levels and correlate these with academic grades. The study employed various scoring metrics, statistical analyses, and dimensionality reduction techniques to uncover meaningful patterns. This updated report incorporates additional analyses from the latest document, particularly focusing on refined scoring metrics and their distributions.

2 Methodology

2.1 Games and Levels

The analysis involved nine cognitive games, each with multiple levels:

- Rain Cloud: Levels 2, 4, 7, 8, 11, 13
- Highway: Levels 1, 11, 21
- Honey Memory: Levels 3, 5, 6, 10, 15, 16, 18
- Tasty Finder: Levels 1, 4, 10, 11, 12
- Control Officer: Levels 3, 9
- Don’t Hit: Levels 1, 2, 9, 10, 11, 12
- Photo Gallery: Levels 2, 5, 6, 10
- Choir Group: Levels 3, 5, 7, 9, 11, 13, 15, 17, 19
- Lost at Sea: Levels 2, 5, 11, 14, 18, 24, 25, 31, 34

2.2 Scoring Metrics

Several scoring metrics were developed to evaluate performance:

1. **B1**: Calculated as:

$$\text{B1} = \frac{\text{Number of Correct} - \text{Number of Incorrect}}{\text{Total Response Time}}$$

   per game level, averaged across individuals.

2. **B2**: Similar to B1, but computed for each attempt within a level, then averaged.

3. **Score**: Direct use of game scores, normalized using z-scores.

4. **Weighted B1**: B1 with coefficients applied to correct and incorrect responses, standardized to mean 0 and variance 1.

5. **Weighted B2**: B2 with similar coefficient weighting.

6. **Sequence-Based Scoring**: For a sequence of responses (e.g., 0 0 1 1 1 1 1 1 0 0 1 1 1 1 1 0 1 1 0 1), the score was computed as:

$$\text{Score} = \frac{\sum_i n_i p^{n_i}}{m p^m}$$

   where $p = \frac{\text{Number of 1s}}{\text{Sequence Length}}$, n_i is the number of consecutive 1s in the i-th block, and m is the total number of 1s. This score was averaged across attempts and prioritized longer sequences in case of ties.

7. **Adjusted B1 (Homogeneous Degree)**: To address the degree mismatch in B1 (where the numerator is the difference of correct and incorrect responses, and the denominator is the sum of response times), a new metric was introduced:

$$\text{Adjusted B1} = \frac{\text{Number of Correct} - \text{Number of Incorrect}}{\text{Sum of Correct Response Times} - \text{Sum of Incorrect Response Times}}$$

   This ensures the numerator and denominator have consistent units.

2.3 Data Preprocessing

- **Z-Score Normalization**: All scores and grades were standardized to z-scores to ensure comparability.
- **Missing Data**: Individuals missing data for more than one level in a game were excluded. Linear regression was used to impute missing data for those missing only one level.
- **Subject Exclusion**: Subjects with sparse participation (e.g., Basketball, Photography, Drama, Pottery, Handball, Gymnastics, Volleyball, Lego, Choir Group) were removed due to insufficient data.
- **Grouping Extracurriculars**: Extracurricular subjects were categorized into "Sports" (e.g., Gymnastics, Basketball) and "Arts" (e.g., Photography, Drama) to address missing data. Each student participated in exactly two subjects from each category.

2.4 Analysis Techniques

- **Correlation Analysis**: Pearson correlations were computed between game scores and academic grades, both with and without considering game levels.
- **Principal Component Analysis (PCA)**: Used to reduce the dimensionality of game scores and grades, extracting key parameters.
- **Response Time Analysis**: Examined the distribution of response times for correct and incorrect answers, with p-values computed to compare distributions across levels.
- **Cognitive Factor Analysis**: Games were grouped by cognitive parameters, and their covariance was analyzed to assess relationships with academic subjects.
- **Distribution Analysis**: Distributions of scoring metrics (B1, Weighted B1, Adjusted B1, etc.) were plotted to assess whether they followed a Gaussian distribution.

3 Results

3.1 Scoring Metrics and Distribution

- **B1 and B2**: Plotting B1 scores across levels revealed non-Gaussian distributions, contrary to expectations that performance would improve or stabilize with higher levels. Applying coefficients to achieve mean 0 and variance 1 (Weighted B1 and B2) did not result in Gaussian distributions, except in one or two isolated cases.
- **Adjusted B1**: The new metric aimed to address the degree mismatch in B1 by using the difference in response times for correct and incorrect answers in the denominator. However, plotting these scores showed that the distributions remained largely non-Gaussian, indicating that the adjustment did not resolve the underlying variability.
- **Sequence-Based Scoring**: Yielded values between 0 and 1 but was sensitive to sequence length and the probability of correct responses. It did not consistently produce Gaussian distributions.
- **Z-Score Analysis**: English grades deviated significantly from a Gaussian distribution, unlike other subjects, suggesting unique characteristics in this subject's data.

3.2 Correlation Findings

- **Game vs. Game**: Correlations between games showed high variability, with no consistent patterns emerging.

- **Game vs. Grade**: Correlations between game scores (including B1, B2, and Adjusted B1) and academic grades were generally low, indicating weak linear relationships.
- **PCA-Based Correlations**: Applying PCA to level scores before correlation analysis yielded results similar to simple averaging, with no significant improvement.

3.3 Response Time Analysis

- No significant difference was found between response times for correct and incorrect answers (97% confidence interval).
- Response time distributions varied significantly across levels within each game (p-values computed for pairwise level comparisons), suggesting level-specific difficulty or engagement factors. For example, games like Tasty Finder and Lost at Sea showed distinct time distributions across levels.

3.4 Cognitive Factor Analysis

- Games were categorized by cognitive parameters, and one parameter was extracted per category. Covariance analysis showed weak relationships with academic subjects.
- Fitting cognitive parameters to training data achieved 56% accuracy, but testing data yielded over 300% error, indicating poor generalizability.

3.5 Subject Grouping

- Grouping extracurricular subjects into Sports and Arts categories reduced missing data issues but did not lead to meaningful correlations with game performance.
- Correlation-based grouping of academic subjects using a threshold (e.g., 0.6) resulted in unintuitive groupings (e.g., Quran-Spelling, Arts-Spelling). Increasing the threshold (e.g., to 0.74 or 0.82) produced even less meaningful groups, such as isolating most subjects independently.

3.6 Parameter Extraction

- PCA was applied to extract parameters from game scores and grades. The first few components explained the most variance, but selecting the optimal number of parameters (e.g., 3 vs. 7) was inconclusive due to high test errors.
- Linear regression and non-linear models (e.g., KNN, polynomial) were used to impute missing game data, with the best-performing model selected.

- Subtracting parameter sets revealed that most individuals exhibited similar behavior, except for one outlier who showed significant deviations in specific subjects (e.g., Heavenly Gifts, Essay).

4 Discussion

The consolidated analysis highlights several key challenges:

- **Non-Linear Relationships**: The consistently low correlations and non-Gaussian distributions of scoring metrics (including the new Adjusted B1) suggest that the relationship between game performance and academic achievement is not linear. Non-linear models or alternative cognitive metrics may be necessary.
- **Distribution Issues**: Efforts to achieve Gaussian distributions through weighting or adjusting metrics (e.g., Adjusted B1) were largely unsuccessful, indicating that the underlying data variability is complex and not easily standardized.
- **Data Sparsity**: Missing data and sparse participation in certain subjects and games complicated the analysis. While imputation helped, it may have introduced biases.
- **Level Variability**: Significant differences in response times and performance across levels suggest that game difficulty or engagement varies, which may confound scoring metrics.
- **Subject Grouping**: Attempts to group subjects based on correlations did not yield psychologically meaningful categories, suggesting that academic subjects may not align neatly with cognitive game performance.

5 Conclusion

Despite extensive efforts to refine scoring metrics (e.g., introducing Adjusted B1) and analyze the relationship between cognitive game performance and academic achievement, a robust linear parameter was not identified. The non-Gaussian distributions, high variability in response times, and weak correlations underscore the complexity of this relationship. Future work should explore non-linear models, incorporate additional cognitive or psychological metrics, and address data sparsity through targeted data collection or alternative experimental designs.