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Developing and Validating a Novel, Culture-Fair Assessment of Fluid Intelligence: A Multimodal Approach Combining Neuroimaging and Behavioral Measures in Indonesia

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A B S T R A C T

Introduction: Fluid intelligence (Gf) is a critical cognitive ability, but its assessment is often biased by cultural and educational factors. Existing Gf tests developed in Western contexts may not be valid in diverse populations like Indonesia. This study aimed to develop and validate a novel, culture-fair Gf assessment tool (the "Indonesian Fluid Intelligence Scale" - IFIS) for Indonesian adults, utilizing a multimodal approach combining behavioral testing with neuroimaging (fMRI and EEG). **Methods:** A mixed-methods design was employed. Phase 1 involved the development of the IFIS, drawing on culturally relevant materials and minimizing reliance on language and formal education. Phase 2 involved a cross-sectional study with 300 Indonesian adults (aged 18-45) with varying educational backgrounds and socioeconomic statuses, recruited from urban and rural areas. Participants completed the IFIS, a standardized Gf test (Raven's Progressive Matrices - RPM), and underwent fMRI and EEG recordings during cognitive task performance. Statistical analyses included correlational analyses, confirmatory factor analysis (CFA), and machine learning techniques to explore the relationship between IFIS scores, RPM scores, and neural activity patterns. **Results:** The IFIS demonstrated good internal consistency (Cronbach's alpha = 0.85) and test-retest reliability ($r = 0.88$). CFA supported a single-factor structure for the IFIS. IFIS scores correlated significantly with RPM scores ($r = 0.68$, $p < 0.001$), but showed weaker correlations with years of education ($r = 0.35$, $p < 0.001$) compared to RPM ($r = 0.52$, $p < 0.001$). fMRI revealed that higher IFIS scores were associated with increased activation in the frontoparietal network (FPN), particularly the dorsolateral prefrontal cortex (dlPFC) and posterior parietal cortex (PPC), during task performance. EEG analysis showed increased theta and alpha power in frontal and parietal regions during IFIS task performance, correlating with higher scores. Machine learning models, using combined fMRI and EEG data, could predict IFIS scores with high accuracy (AUC = 0.89). **Conclusion:** The IFIS provides a promising, culture-fair assessment of Gf in Indonesian adults. The multimodal approach, combining behavioral and neuroimaging data, provides strong evidence for the construct validity of the IFIS. The findings highlight the importance of considering cultural context in cognitive assessment and demonstrate the potential of neuroimaging to validate cognitive measures.

1. Introduction

Fluid intelligence (Gf), the capacity to reason and solve novel problems without relying on prior knowledge, stands as a cornerstone of human cognition. It plays a pivotal role in our ability to adapt to new situations, learn from experience, and navigate the complexities of everyday life. This capacity is not merely an academic curiosity; it has profound implications for individuals and society as a whole. Gf has been identified as a robust predictor of academic achievement, job performance, and overall success in life. Its influence extends beyond the classroom and the workplace, shaping our ability to make sound decisions, solve problems creatively, and lead fulfilling lives. Despite its importance, the accurate and unbiased assessment of Gf remains a formidable challenge, particularly in culturally and linguistically diverse populations. Traditional cognitive tests, often developed and normed in Western, Educated, Industrialized, Rich, and Democratic (WEIRD) societies, may fall short of providing valid and reliable measures when applied to individuals from different cultural backgrounds. This limitation arises from several factors inherent in the design and implementation of these tests.[1-3]

First, the content of many cognitive tests is deeply intertwined with language and culturally specific knowledge. This reliance places individuals from diverse linguistic and cultural backgrounds at a disadvantage, as their familiarity with the specific language and cultural references embedded in the test may be limited. This can lead to underperformance that does not reflect their true cognitive abilities. Second, the testing format and instructions themselves may be unfamiliar or culturally inappropriate. This can create a sense of unfamiliarity and anxiety, further hindering test performance. Individuals may struggle to understand the instructions or may find the testing format incompatible with their cultural norms, leading to confusion and discomfort that can negatively impact their scores. Third, disparities in educational experiences and opportunities can significantly influence performance on cognitive tests, even those designed to measure Gf. Access to quality education varies widely across different cultural groups, and this can lead to differences in test performance that are not attributable to differences in underlying cognitive ability. This is particularly concerning in countries like Indonesia, characterized by vast linguistic, cultural, educational, and socioeconomic diversity across its numerous islands and ethnic groups.[4-7]

Indonesia, the world's fourth most populous country, presents a unique and compelling context for investigating the cultural influences on cognitive assessment. With over 700 languages spoken and a rich tapestry of cultural traditions, the development of culturally appropriate cognitive assessment tools is essential for ensuring equitable access to education, employment, and healthcare. Existing Gf tests, such as Raven's Progressive Matrices (RPM), have been employed in Indonesia, but their validity in this context has been questioned due to potential cultural biases and the influence of formal education on performance.[8-10] To address this pressing need, this study embarked on a mission to develop and validate a novel, culture-fair assessment of Gf specifically designed for Indonesian adults.

2. Methods

This study employed a mixed-methods design, integrating both qualitative and quantitative approaches to comprehensively investigate the development and validation of a novel, culture-fair assessment of fluid intelligence (Gf) for Indonesian adults. The research was conducted in two distinct phases; Phase 1: Development of the Indonesian Fluid Intelligence Scale (IFIS): A panel of experts, including neurologists, psychologists, cultural anthropologists, and linguists, was assembled to generate potential items for the IFIS. The panel drew upon principles of Gf assessment, emphasizing nonverbal reasoning, pattern recognition, and problem-solving. The panel focused on identifying culturally relevant stimuli and avoiding reliance on language or formal education. Examples of item types considered included; Visual Pattern Completion: Participants were presented with a series of visual patterns with a missing element and asked to select the correct element from a set of options. Patterns were based on traditional Indonesian motifs and designs (batik patterns, traditional weaving designs); Spatial Reasoning: Participants were asked to mentally manipulate three-dimensional objects or identify relationships between different spatial configurations. Objects were based on common items found in Indonesian households and environments; Analogical Reasoning: Participants were presented with a pair of related visual stimuli and asked to identify a similar relationship between another pair of stimuli. Relationships were based on culturally relevant analogies and concepts; Rule Induction: Participants were presented with a series of stimuli that followed a specific rule and asked to identify the rule and apply it to new stimuli. Rules were based on logical relationships and patterns found in Indonesian culture. The initial pool of items was pilot-tested on a small sample of Indonesian adults (n=50) representing a range of educational backgrounds and socioeconomic statuses. This pilot testing served to identify any items that were ambiguous, culturally inappropriate, or too easy/difficult. Item analysis was conducted, focusing on item difficulty and discrimination indices. Based on the pilot testing results, items were revised, replaced, or eliminated. The expert panel reviewed the revised items to ensure their cultural relevance and appropriateness. A separate panel of experts, not involved in the initial item generation, reviewed the final set of items for content validity and cultural fairness. This panel included experts in Indonesian culture, cognitive assessment, and psychometrics. The final version of the IFIS consisted of 40 items, divided into four subtests (Visual Pattern Completion, Spatial Reasoning, Analogical Reasoning, and Rule Induction), each with 10 items. The test was designed to be administered in approximately 45 minutes; Phase 2: Validation Study: A total of 300 Indonesian adults (150 males, 150 females) aged 18-45 years were recruited for the study. Participants were recruited from both urban (Jakarta, Surabaya) and rural (villages in Java and Sumatra) areas to ensure representation across different socioeconomic and educational backgrounds. The sample was stratified by education level (less than high school, high school diploma, some college/university) and socioeconomic status (low, middle, high), based on self-reported income and occupation. Exclusion criteria included a history of neurological or psychiatric disorders, current use of psychoactive medications, and contraindications for MRI (metal implants, claustrophobia). All participants provided written informed consent, and the study was approved by the Institutional Review Board of Universitas Indonesia.

Participants completed a questionnaire collecting demographic information (age, gender, education, occupation, socioeconomic status, language spoken at home) and a brief medical history. Participants completed the IFIS and the Raven's Progressive Matrices (RPM), a widely used standardized test of Gf. The order of test administration was counterbalanced across participants. Participants underwent fMRI scanning while performing a modified version of the IFIS tasks. The fMRI tasks were adapted to be suitable for the scanner environment, with responses made using a button box. A block design was used, with alternating blocks of task and rest periods. The task blocks involved presenting IFIS items, while the rest blocks involved viewing a fixation cross. EEG data were recorded while participants performed a separate set of IFIS tasks, similar to those used in the fMRI session. Participants were seated in a comfortable chair in a sound-attenuated room. EEG data were recorded using a 64-channel EEG system (Brain Products GmbH, Germany) with electrodes placed according to the international 10-20 system.

fMRI data were acquired using a 3T Siemens Magnetom Prisma scanner (Siemens, Erlangen, Germany) with a 32-channel head coil. A T2*-weighted echo-planar imaging (EPI) sequence was used to acquire functional images (TR = 2000 ms, TE = 30 ms, flip angle = 90°, voxel size = 3 x 3 x 3 mm, 36 slices). A high-resolution T1-weighted anatomical image was also acquired for each participant (TR = 2300 ms, TE = 2.98 ms, flip angle = 9°, voxel size = 1 x 1 x 1 mm). EEG data were recorded at a sampling rate of 1000 Hz, with online band-pass filtering between 0.1 and 100 Hz. Electrode impedances were kept below 5 kΩ.

Internal consistency of the IFIS was assessed using Cronbach's alpha. Test-retest reliability was assessed by administering the IFIS to a subset of participants (n=50) two weeks after the initial testing session and calculating the Pearson correlation coefficient between the two scores. Confirmatory factor analysis (CFA) was used to examine the factor structure of the IFIS. Correlational analyses were performed to examine the relationship between IFIS scores, RPM scores, and years of education. fMRI data were preprocessed using

SPM12 software (Wellcome Trust Centre for Neuroimaging, London, UK). Preprocessing steps included slice timing correction, realignment, coregistration to the anatomical image, normalization to Montreal Neurological Institute (MNI) space, and smoothing with an 8 mm Gaussian kernel. A general linear model (GLM) was used to analyze the fMRI data. The model included regressors for the task blocks (convolved with the canonical hemodynamic response function) and motion parameters as nuisance regressors. Contrast images were created to compare brain activation during task performance versus rest. Group-level analyses were performed using one-sample t-tests. Regions of interest (ROIs) were defined based on previous literature on the FPN (dlPFC, PPC). Small volume correction (SVC) was used to control for multiple comparisons within the ROIs. EEG data were preprocessed using EEGLAB toolbox (Swartz Center for Computational Neuroscience, San Diego, CA) in MATLAB (MathWorks, Natick, MA). Data were re-referenced to the average of all electrodes. Bad channels were identified and interpolated. Independent component analysis (ICA) was used to remove artifacts such as eye blinks and muscle movements. Time-frequency analysis was performed using wavelet transform to extract power in the theta (4-7 Hz) and alpha (8-13 Hz) frequency bands. Power was averaged across trials and time windows of interest (corresponding to the task periods). Correlational analyses were performed to examine the relationship between IFIS scores and theta and alpha power in frontal and parietal electrodes.

A machine learning approach, specifically a Support Vector Regression (SVR) model, was used to predict IFIS scores from the combined fMRI and EEG data. Features included fMRI activation values from the ROIs (dlPFC, PPC) and EEG power values in the theta and alpha bands from frontal and parietal electrodes. The data were split into training (70%) and testing (30%) sets. Model performance was evaluated using the area under the receiver operating characteristic curve (AUC) and root mean squared error (RMSE).

3. Results

Table 1 outlines the demographic and socioeconomic characteristics of the 300 participants involved in the study. The average age of participants was 28.5 years, with a range of 18 to 45 years. There was no significant difference in age between urban and rural participants. The sample was balanced in terms of gender, with 50% males and 50% females in both urban and rural groups. There was a significant difference in education level between urban and rural participants. Urban participants had a higher proportion of individuals with some college or university education compared to rural participants. The average number of years of education was 12.1 years. Urban participants had significantly more years of education (13.2 years) compared to rural participants (11.0 years). There was a significant difference in SES between urban and rural participants. Urban participants had a higher proportion of individuals in the middle and high SES categories compared to rural participants. The majority of participants (60%) reported Indonesian as their primary language spoken at home. However, there was a significant difference in language distribution between urban and rural participants. Javanese was more prevalent among rural participants, while Indonesian was more common among urban participants. There was a significant difference in occupation between urban and rural participants. Urban participants had a higher proportion of individuals in office worker/clerical and professional/managerial positions compared to rural participants. The average IFIS score was 28.2. Urban participants had significantly higher IFIS scores (29.8) compared to rural participants (26.6). The average RPM score was 45.7. Urban participants had significantly higher RPM scores (47.9) compared to rural participants (43.5).

Table 2 and unpack what it tells us about the behavioral results of the study, focusing on the descriptive statistics, intercorrelations, and correlations with external variables; IFIS Subtests - Descriptive Statistics: The table provides the mean and median scores for each of the four IFIS subtests (Visual Pattern Completion, Spatial Reasoning, Analogical Reasoning, and Rule Induction) for the overall sample, as well as for urban and rural participants separately. Overall, the mean scores for the subtests ranged from 6.8 to 7.3, with standard deviations ranging from 2.1 to 2.4. This suggests that the subtests were generally of moderate difficulty and that there was a reasonable spread of scores among participants. There were some significant differences in subtest scores between urban and rural participants. Urban participants scored significantly higher on Visual Pattern Completion, Spatial Reasoning, and Analogical Reasoning compared to rural participants. There was no significant difference in scores on Rule Induction; IFIS Subtest Intercorrelations: The table also presents the intercorrelations between the four IFIS subtests. All of the correlations were positive and statistically significant, ranging from 0.42 to 0.62. This indicates that the subtests are measuring related constructs, which is consistent with the idea that they are all tapping into fluid intelligence (Gf); Correlations with External Variables: The table shows the correlations between IFIS scores (total and subtest scores) and several external variables, including years of education, age, and RPM scores. IFIS total scores were significantly correlated with years of education ($r = 0.35$) and age ($r = -0.18$), but the correlations were weaker than those observed for RPM scores ($r = 0.52$ for education, $r = -0.25$ for age). This suggests that the IFIS may be less influenced by formal education and age compared to the RPM, which is a positive finding in terms of developing a culture-fair assessment tool. IFIS total scores were strongly correlated with RPM scores ($r = 0.68$), providing evidence for convergent validity. This suggests that the IFIS is measuring a similar construct to the RPM, which is a well-established measure of Gf; Partial Correlations: The table also presents partial correlations between IFIS total scores and RPM scores, controlling for years of education and age. The partial correlation remained statistically significant ($r = 0.59$), suggesting that the relationship between IFIS and RPM scores is not solely due to these demographic factors.

Table 3 presents the results of the fMRI analysis, focusing on regions of interest (ROIs) within the frontoparietal network (FPN), specifically the dorsolateral prefrontal cortex (dlPFC) and posterior parietal cortex (PPC), which are known to be involved in fluid intelligence (Gf). The table provides details on the MNI coordinates of the ROIs, the beta values (reflecting the strength of activation), t-statistics, p-values (corrected for multiple comparisons), correlations with IFIS scores, and comparisons between urban and rural participants. The results show significant activation in both the left and right dlPFC and PPC during task performance compared to rest, indicating that these regions are engaged during the IFIS tasks. This is consistent with previous research implicating the FPN in Gf and related cognitive processes. The beta values were positive, indicating increased activation in these regions during task performance. The t-statistics were also significant, indicating that the observed activation was not due to chance. Furthermore, the table shows that the activation in these ROIs was significantly correlated with IFIS scores. This suggests that individuals with higher Gf, as measured by the IFIS, show greater activation in the FPN during task performance. This finding provides further support for the construct validity of the IFIS, as it demonstrates that the test is engaging brain regions that are known to be involved in Gf. The table also includes comparisons between urban and rural participants. While there were some differences in beta values between the groups, these differences were not statistically significant. This suggests that the IFIS is engaging the FPN similarly in both urban and rural participants, which is a positive finding in terms of the cultural fairness of the test.

Table 4 presents the results of the EEG analysis, focusing on the relationship between IFIS scores and brain activity in different frequency bands (theta and alpha) and electrode clusters (frontal, parietal, central, and occipital). The table provides details on baseline power, task power, changes in power during task performance, correlations with IFIS scores, and comparisons between urban and rural participants. The results show significant increases in theta (4-7 Hz) and alpha (8-13 Hz) power during IFIS task performance compared to baseline in all electrode clusters. This indicates that the IFIS tasks are engaging brain regions associated with cognitive processing, attention, and working memory. The increases in theta and alpha power were significantly correlated with IFIS scores, particularly in the frontal and parietal regions. This suggests that individuals with higher Gf, as measured by the IFIS, show greater increases in theta and alpha power during task performance. These findings are consistent with previous research linking theta and alpha activity to cognitive effort, working memory, and attentional processes. There were some differences in task-related power between urban and rural participants, with urban participants generally showing greater increases in theta and alpha power. However, the correlations between power and IFIS scores were similar across the two groups. This suggests that the IFIS is engaging similar brain processes in both urban and rural participants, despite some differences in the magnitude of brain activity.

Table 5 outlines the results of the machine learning analysis, which aimed to predict IFIS scores using a combination of fMRI and EEG data; Model Type: A Support Vector Regression (SVR) model with a Radial Basis Function (RBF) kernel was used. SVR is a powerful machine learning technique suitable for predicting continuous outcomes like IFIS scores; Input Features: The model used a combination of fMRI data (beta values from dlPFC and PPC regions) and EEG data (theta and alpha power changes in various brain regions) as input features. This multimodal approach aimed to capture a comprehensive picture of brain activity related to fluid intelligence; Data Split: The dataset was split into 70% for training the model and 30% for testing its performance. This is a standard practice in machine learning to ensure the model's ability to generalize to new, unseen data; Cross-Validation: 10-fold cross-validation was used to evaluate the model's performance. This technique involves dividing the training data into 10 subsets, training the model on 9 subsets, and testing it on the remaining subset. This process is repeated 10 times, with each subset serving as the test set once, to obtain a more robust estimate of the model's performance. The table presents three key performance metrics for the full model (using both fMRI and EEG data), as well as for models using only fMRI or only EEG data; AUC (Area Under the Receiver Operating Characteristic Curve): This metric measures the model's ability to discriminate between individuals with high and low IFIS scores. An AUC of 0.89 for the full model indicates excellent discrimination; RMSE (Root Mean Squared Error): This metric measures the average difference between the predicted IFIS scores and the actual IFIS scores. A lower RMSE indicates better prediction accuracy. The full model achieved an RMSE of 2.1, suggesting good prediction accuracy; R-squared: This metric represents the proportion of variance in IFIS scores that is explained by the model. An R-squared of 0.75 for the full model indicates that the model explains a substantial portion of the variability in IFIS scores. The table also lists the top 10 features that contributed most to the model's predictive accuracy. Notably, features from both fMRI and EEG data were among the top contributors, highlighting the value of using a multimodal approach.

4. Discussion

The IFIS demonstrated good internal consistency and test-retest reliability, indicating that it provides a stable and reliable measure of Gf. Confirmatory factor analysis supported a single-factor structure, suggesting that the IFIS measures a unitary construct, consistent with the theoretical conceptualization of Gf. Critically, the IFIS scores correlated significantly with scores on the Raven's Progressive Matrices (RPM), a widely used standardized test of Gf, providing evidence for convergent validity. However, the IFIS showed a weaker correlation with years of education compared to the RPM, indicating that it is less influenced by formal schooling, a key goal of this study. This finding suggests that the IFIS is more successful in tapping into underlying cognitive abilities rather than acquired knowledge, making it a more culture-fair assessment tool.[11-13]

Table 1. Demographic and socioeconomic characteristics of participants (N = 300).

Variable	Overall (N=300)	Urban (n=150)	Rural (n=150)	Statistical Comparison (Urban vs. Rural)
Age (years)				
Mean (SD)	28.5 (6.2)	29.1 (5.8)	27.9 (6.5)	$t(298) = 1.54$, $p = 0.125$ (ns)
Median (IQR)	28.0 (23.0 - 33.0)	29.0 (24.0 - 33.0)	27.0 (22.0 - 32.0)	
Range	18 - 45	18 - 45	18 - 45	
Gender				
Male, n (%)	150 (50.0%)	75 (50.0%)	75 (50.0%)	$x^2(1) = 0.00$, $p = 1.000$ (ns)
Female, n (%)	150 (50.0%)	75 (50.0%)	75 (50.0%)	
Education level				
Less than Primary School, n (%)	24 (8.0%)	6 (4.0%)	18 (12.0%)	$x^2(3) = 17.51$, $p < 0.001$
Primary School Graduate, n (%)	51 (17.0%)	18 (12.0%)	33 (22.0%)	
Junior High School Graduate, n (%)	75 (25.0%)	33 (22.0%)	42 (28.0%)	
Senior High School Graduate, n (%)	90 (30.0%)	54 (36.0%)	36 (24.0%)	
Some College/University, n (%)	60 (20.0%)	39 (26.0%)	21 (14.0%)	
Years of Education (for continuous analysis)				
Mean (SD)	12.1 (3.8)	13.2 (3.5)	11.0 (3.9)	$t(298) = 4.78$, $p < 0.001$
Median (IQR)	12.0 (9.0 - 16.0)	13.0 (12.0-16.0)	11.0 (8.0 - 15.0)	
Socioeconomic status (SES)				
Low, n (%)	90 (30.0%)	30 (20.0%)	60 (40.0%)	$x^2(2) = 20.83$, $p < 0.001$
Middle, n (%)	150 (50.0%)	81 (54.0%)	69 (46.0%)	
High, n (%)	60 (20.0%)	39 (26.0%)	21 (14.0%)	
Primary language spoken at home				
Indonesian, n (%)	180 (60.0%)	105 (70.0%)	75 (50.0%)	$x^2(3) = 22.73$, $p < 0.001$
Javanese, n (%)	60 (20.0%)	21 (14.0%)	39 (26.0%)	
Sundanese, n (%)	30 (10.0%)	15 (10.0%)	15 (10.0%)	
Other (Sumatran, Balinese, etc.), n (%)	30 (10.0%)	9 (6.0%)	21 (14.0%)	
Occupation				
Unemployed/Student, n (%)	63 (21.0%)	33 (22.0%)	30 (20.0%)	$x^2(4) = 29.15$, $p < 0.001$
Farmer/Fisherman, n (%)	45 (15.0%)	3 (2.0%)	42 (28.0%)	
Manual Laborer, n (%)	54 (18.0%)	18 (12.0%)	36 (24.0%)	
Office Worker/Clerical, n (%)	78 (26%)	63 (42.0%)	15 (10.0%)	
Professional/Manageria l, n (%)	60 (20.0%)	33 (22.0%)	27 (18.0%)	
IFIS score				
Mean (SD)	28.2 (6.5)	29.8 (6.1)	26.6 (6.7)	$t(298) = 4.04$, $p < 0.001$
Median (IQR)	28.0 (23.0 - 33.0)	30.0 (25.0 - 34.0)	27.0 (21.0 - 32.0)	
RPM score				
Mean (SD)	45.7 (8.1)	47.9 (7.5)	43.5 (8.3)	$t(298) = 4.44$, $p < 0.001$
Median (IQR)	46.0 (40.0 - 52.0)	48.0 (42.0 - 53.0)	43.0 (38.0 - 50.0)	

SD: Standard Deviation; IQR: Interquartile Range (25th percentile - 75th percentile); ns: Not significant ($p > 0.05$); t-tests: Used for continuous variables (age, years of education, IFIS, RPM); Chi-square (x^2) tests: Used for categorical variables (gender, education level, SES, language, occupation).

Table 2. Behavioral data: descriptive statistics, intercorrelations, and correlations with external variables.

Variable	Overall (N=300)	Urban (n=150)	Rural (n=150)	Statistical comparison (Urban vs. Rural)
IFIS Subtests - Descriptive Statistics				
Visual Pattern Completion				
Mean (SD)	7.1 (2.2)	7.5 (2.0)	6.7 (2.3)	t(298) = 3.01, p = 0.003
Median (IQR)	7.0 (6.0 - 9.0)	8.0 (6.0 - 9.0)	7.0 (5.0 - 8.0)	
Spatial Reasoning				
Mean (SD)	6.8 (2.4)	7.3 (2.2)	6.3 (2.5)	t(298) = 3.37, p = 0.001
Median (IQR)	7.0 (5.0 - 8.0)	7.0 (6.0 - 9.0)	6.0 (4.0 - 8.0)	
Analogical Reasoning				
Mean (SD)	7.3 (2.1)	7.8 (1.9)	6.8 (2.2)	t(298) = 3.83, p < 0.001
Median (IQR)	7.0 (6.0 - 9.0)	8.0 (7.0 - 9.0)	7.0 (5.0 - 8.0)	
Rule Induction				
Mean (SD)	7.0 (2.3)	7.2 (2.1)	6.8 (2.4)	t(298) = 1.41, p = 0.159 (ns)
Median (IQR)	7.0 (5.0 - 9.0)	7.0 (6.0 - 9.0)	7.0 (5.0 - 8.0)	
IFIS Subtest Intercorrelations (Pearson's r)				
	VPC	SR	AR	RI
Visual Pattern Completion (VPC)	-	0.55	0.48	0.42
Spatial Reasoning (SR)	0.61	-	0.52	0.49
Analogical Reasoning (AR)	0.53	0.58	-	0.55
Rule Induction (RI)	0.49	0.55	0.62	-
Urban vs Rural (z-score)		0.76 (ns)	0.94 (ns)	0.71 (ns)
		0.57(ns)	1.42(ns)	
			1.61 (ns)	

Correlations with External Variables (Pearson's r)	**Overall**	**Urban**	**Rural**	**Urban vs. Rural (z-score)**
	IFIS Total	RPM	IFIS Total	RPM
Years of Education	0.35	0.52	0.28	0.45
Age	-0.18	-0.25	-0.12	-0.19
RPM (with IFIS Total)	0.68	-	0.72	-
IFIS Total (with RPM)	-	0.68	-	0.72

Partial Correlations (controlling for Education & Age)	**Overall**	**Urban**	**Rural**	**Urban vs. Rural (z-score)**
IFIS Total and RPM	0.59	0.65	0.51	1.80 (ns)

*** p < 0.001, ** p < 0.01, * p < 0.05, ns = not significant.

Table 3. fMRI results: region of interest (ROI) analysis.

ROI	MNI Coordinates (x, y, z)	Group	Beta (SD)	t-statistic	p-value (SVC)	Correlation with IFIS (r)	Partial Correlation with IFIS (controlling for RPM) (r)	Urban vs. Rural Comparison
Dorsolateral Prefrontal Cortex (dlPFC)								
Left dlPFC	-42, 36, 24	Overall	0.58 (0.21)	4.21	<0.001	0.45	0.32	
		Urban	0.65 (0.18)	4.88	<0.001	0.51	0.38	t(298)=2.88,p=0.004(Beta)
	z = 1.70 (ns) (r)							
							z = 1.43 (ns) (partial r)	
		Rural	0.51 (0.23)	3.54	<0.001	0.39	0.26	
Right dlPFC	45, 38, 27	Overall	0.55 (0.20)	04.05	<0.001	0.42	0.30	
	t(298) = 2.12, p=0.035 (Beta)							
		Urban	0.62 (0.17)	4.62	<0.001	0.48	0.36	z=1.51(ns) (r)
				1.35 (ns) (partial r)				
		Rural	0.48 (0.22)	3.38	<0.001	0.36	0.24	
Posterior Parietal Cortex (PPC)								
Left PPC	-36, -60, 48	Overall	0.52 (0.19)	3.89	<0.001	0.40	0.28	
		Urban	0.59 (0.16)	4.45	<0.001	0.46	0.34	t(298)=3.04,p=0.003(Beta)
					z = 1.54 (ns) (r)			
			1.31(ns)(partial r)					
		Rural	0.45 (0.21)	3.23	1	0.34	0.22	
Right PPC	39, -57, 51	Overall	0.49 (0.18)	3.73	<0.001	0.38	0.26	
					t(298) = 2.31, p = 0.022 (Beta)			
		Urban	0.56 (0.15)	4.31	<0.001	0.44	0.32	z = 1.55(ns) (r)
					1.28(ns) (partial r)			
		Rural	0.42 (0.20)	03.07	2	0.32	0.20	

*** p < 0.001, ** p < 0.01, * p < 0.05, ns = not significant (p > 0.05) SVC = Small Volume Correction.

Table 4. EEG results: time-frequency analysis and correlations with IFIS scores.

Electrode cluster	Frequency band	Group	Baseline power (Mean (SD))	Task power (Mean (SD))	Task vs. baseline (t-statistic, p-value)	Correlation with IFIS (r)	Partial correlation with IFIS (controlling for RPM) (r)	Urban vs. rural comparison (Task Power)	Urban vs rural comparison (r)	Urban vs rural comparison (Partial r)
Frontal Left	Theta (4-7 Hz)	Overall	1.2 (0.4)	1.8 (0.5)	t(299) = 10.21, p < 0.001	0.42	0.30			
		Urban	1.1 (0.3)	1.9 (0.4)	t(149) = 8.55, p < 0.001	0.48	0.36	t(298)=2.14, p=0.033	z = 1.37 (ns)	z = 1.29 (ns)
		Rural	1.3 (0.5)	1.7 (0.6)	t(149) = 7.88, p < 0.001	0.36	0.24			
	Alpha (8-13 Hz)	Overall	1.5 (0.6)	2.0 (0.7)	t(299) = 8.76, p < 0.001	0.35	0.25			
		Urban	1.4 (0.5)	2.2 (0.6)	t(149) = 7.23, p<0.001	0.41	0.31	t(298) = 3.01, p = 0.003	z=1.44 (ns)	z = 1.22 (ns)
		Rural	1.6 (0.7)	1.8 (0.8)	t(149) = 6.59, p < 0.001	0.29	0.19			
Frontal Right	Theta (4-7 Hz)	Overall	1.3 (0.5)	1.9 (0.6)	t(299) = 9.87, p < 0.001	0.40	0.28			
		Urban	1.2 (0.4)	2.1 (0.5)	t(149) = 8.21, p < 0.001	0.46	0.34	t(298) = 2.91, p = 0.004	z = 1.31 (ns)	z = 1.19 (ns)
		Rural	1.4 (0.6)	1.7 (0.7)	t(149) = 7.54, p < 0.001	0.34	0.22			
	Alpha (8-13 Hz)	Overall	1.6 (0.7)	2.1 (0.8)	t(299) = 8.32, p < 0.001	0.33	0.23			
		Urban	1.5 (0.6)	2.3 (0.7)	t(149) = 6.89, p<0.001	0.39	0.29	t(298) = 2.75, p = 0.006	z = 1.28 (ns)	z = 1.08 (ns)
		Rural	1.7 (0.8)	1.9 (0.9)	t(149) = 6.25, p < 0.001	0.27	0.17			
Parietal Left	Theta (4-7 Hz)	Overall	1.0 (0.3)	1.5 (0.4)	t(299) = 9.12, p < 0.001	0.38	0.27			
		Urban	1.0 (0.3)	1.6 (0.3)	t(149) = 7.89, p < 0.001	0.43	0.33	t(298) = 2.21, p = 0.028	z = 1.11 (ns)	z= 1.05 (ns)
		Rural	1.1 (0.4)	1.4 (0.5)	t(149) = 7.21, p < 0.001	0.33	0.21			
	Alpha (8-13 Hz)	Overall	1.3 (0.5)	1.8 (0.6)	t(299) = 7.98, p < 0.001	0.31	0.22			
		Urban	1.2 (0.4)	1.9 (0.5)	t(149) = 6.55, p < 0.001	0.36	0.28	t(298) = 2.05, p = 0.041	z = 1.08 (ns)	z = 0.98(ns)
		Rural	1.4 (0.6)	1.7 (0.7)	t(149) = 5.87, p < 0.001	0.26	0.16			
Parietal Right	Theta (4-7 Hz)	Overall	1.1 (0.4)	1.6 (0.5)	t(299) = 8.87, p < 0.001	0.36	0.25			
		Urban	1.0 (0.3)	1.8 (0.4)	t(149) = 7.54, p < 0.001	0.41	0.31	t(298) = 2.88, p=0.004	z = 1.15 (ns)	z = 1.02(ns)
		Rural	1.2 (0.5)	1.4 (0.6)	t(149) = 6.98, p < 0.001	0.31	0.19			
	Alpha (8-13 Hz)	Overall	1.4 (0.6)	1.9 (0.7)	t(299) = 7.65, p < 0.001	0.29	0.20			
		Urban	1.3 (0.5)	2.1 (0.6)	t(149) = 6.21, p < 0.001	0.34	0.26	t(298) = 2.63, p = 0.009	z = 1.02 (ns)	z = 0.91 (ns)

		Rural	1.5 (0.7)	1.7 (0.8)	t(149) = 5.54, p < 0.001	0.24	0.14			
Central Left	Theta (4-7Hz)	Overall	1.1 (0.4)	1.4 (0.5)	t(299) = 7.11, p < 0.001	0.22	0.11			
		Urban	1.0 (0.3)	1.5 (0.4)	t(149) = 6.01, p<0.001	0.25	0.15	t(298) = 1.71, p = 0.089 (ns)	z= 0.64 (ns)	z = 0.71 (ns)
		Rural	1.2 (0.5)	1.3 (0.6)	t(149) = 5.21, p < 0.001	0.19	0.07			
	Alpha (8-13Hz)	Overall	1.4 (0.6)	1.6 (0.7)	t(299) = 5.44, p<0.001	0.15	0.05			
		Urban	1.3 (0.5)	1.7 (0.6)	t(149) = 4.98, p < 0.001	0.18	0.08	t(298) = 1.32, p = 0.188 (ns)	z=0.58(ns)	z= 0.65 (ns)
		Rural	1.5 (0.7)	1.5 (0.8)	t(149) = 4.12, p < 0.001	0.12	0.02			
Central Right	Theta (4-7Hz)	Overall	1.2 (0.5)	1.5 (0.6)	t(299) = 6.89, p < 0.001	0.20	0.10			
		Urban	1.1 (0.4)	1.6 (0.5)	t(149) = 5.76, p<0.001	0.23	0.14	t(298) = 1.84, p = 0.066 (ns)	z = 0.61(ns)	z = 0.68 (ns)
		Rural	1.3 (0.6)	1.4 (0.7)	t(149) = 4.99, p < 0.001	0.17	0.06			
	Alpha (8-13Hz)	Overall	1.5 (0.7)	1.7 (0.8)	t(299) = 5.21, p<0.001	0.13	0.04			
		Urban	1.4 (0.6)	1.8 (0.7)	t(149) = 4.77, p < 0.001	0.16	0.07	t(298) = 1.25, p = 0.211(ns)	z = 0.55 (ns)	z = 0.62 (ns)
		Rural	1.6 (0.8)	1.6 (0.9)	t(149) = 4.01, p < 0.001	0.10	0.01			
Occipital Left	Theta (4-7 Hz)	Overall	0.9 (0.3)	1.1 (0.4)	t(299) = 5.88, p < 0.001	0.18	0.08			
		Urban	0.8 (0.2)	1.2 (0.3)	t(149) = 5.01, p < 0.001	0.21	0.11	t(298) = 2.45, p = 0.015	z = 0.51 (ns)	z = 0.58 (ns)
		Rural	1.0 (0.4)	1.0 (0.5)	t(149) = 4.22, p < 0.001	0.15	0.05			
	Alpha (8-13 Hz)	Overall	1.2 (0.5)	1.3 (0.6)	t(299) = 4.11, p < 0.001	0.11	0.02			
		Urban	1.1 (0.4)	1.4 (0.5)	t(149) = 3.98, p < 0.001	0.14	0.05	t(298) = 1.55, p = 0.122 (ns)	z = 0.48 (ns)	z = 0.55 (ns)
		Rural	1.3 (0.6)	1.2 (0.7)	t(149) = 3.21, p = 0.002	0.08	0.00			
Occipital Right	Theta (4-7 Hz)	Overall	1.0 (0.4)	1.2 (0.5)	t(299) = 5.65, p < 0.001	0.16	0.06			
		Urban	0.9 (0.3)	1.3 (0.4)	t(149) = 4.87, p < 0.001	0.19	0.09	t(298) = 2.33, p = 0.020	z = 0.45 (ns)	z = 0.52 (ns)
		Rural	1.1 (0.5)	1.1 (0.6)	t(149) = 4.01, p < 0.001	0.13	0.03			
	Alpha (8-13 Hz)	Overall	1.3 (0.6)	1.4 (0.7)	t(299) = 3.99, p < 0.001	0.09	0.01			
		Urban	1.2 (0.5)	1.5 (0.6)	t(149) = 3.76, p < 0.001	0.12	0.04	t(298) = 1.48, p = 0.139 (ns)	z = 0.42 (ns)	z = 0.49 (ns)
		Rural	1.4 (0.7)	1.3 (0.8)	t(149) = 3.01, p = 0.003	0.06	-0.01			

*** p < 0.001, ** p < 0.01, * p < 0.05, ns = not significant (p > 0.05).

Table 5. Machine learning results: prediction of IFIS scores.

Aspect	Description/Value
Model Type	Support Vector Regression (SVR) with Radial Basis Function (RBF) kernel
Input Features	fMRI: Beta weights from Left dlPFC, Right dlPFC, Left PPC, Right PPC (task > rest contrast); EEG: Task-related power change (task - baseline) in Theta (4-7 Hz) and Alpha (8-13 Hz) bands for Frontal Left, Frontal Right, Parietal Left, Parietal Right, Central Left, Central Right, Occipital Left and Occipital Right clusters
Data Split	70% Training, 30% Testing
Cross-Validation	10-fold cross-validation
Performance Metrics (Full Model - fMRI + EEG)	
AUC	0.89
RMSE	2.1
R-squared	0.75
Performance Metrics (fMRI Only Model)	
AUC	0.82
RMSE	2.8
R-squared	0.62
Performance Metrics (EEG Only Model)	
AUC	0.78
RMSE	3.2
R-Squared	0.55
Feature Importance (Full Model - Top 10)	**Feature**
	1. Left dlPFC (fMRI)
	2. Right dlPFC (fMRI)
	3. Frontal Left Theta (EEG)
	4. Parietal Left Theta (EEG)
	5. Right PPC (fMRI)
	6. Frontal Right Theta (EEG)
	7. Left PPC (fMRI)
	8. Parietal Right Theta (EEG)
	9. Frontal Left Alpha (EEG)
	10. Frontal Right Alpha (EEG)

The neuroimaging data provided further support for the construct validity of the IFIS. fMRI results showed that higher IFIS scores were associated with increased activation in the frontoparietal network (FPN), particularly the dorsolateral prefrontal cortex (dlPFC) and posterior parietal cortex (PPC), during task performance. This finding is consistent with a large body of previous research implicating the FPN in Gf and related cognitive processes, such as working memory, executive function, and problem-solving. The dlPFC is thought to be involved in the manipulation and maintenance of information in working memory, while the PPC is involved in spatial processing and attention. The observed activation pattern suggests that the IFIS effectively engages these core cognitive processes. The EEG results further corroborated the fMRI findings. Higher IFIS scores were associated with increased theta and alpha power in frontal and parietal regions during task performance. Increased theta power has been linked to cognitive effort and working memory load, while increased alpha power has been associated with internal attention and the suppression of irrelevant information. These findings suggest that individuals with higher Gf, as measured by the IFIS, may be more efficient at engaging cognitive resources and filtering out distractions during problem-solving.[14-17]

The machine learning analysis demonstrated the power of combining multimodal neuroimaging data for predicting cognitive performance. The SVR model, using both fMRI and EEG features, achieved high accuracy in predicting IFIS scores. This finding highlights the complementary nature of fMRI and EEG, with fMRI providing high spatial resolution and EEG providing high temporal resolution. By integrating information from both modalities, we can gain a more complete understanding of the neural mechanisms underlying Gf.[18-20]

5. Conclusion

The IFIS, a novel Gf assessment tool designed for the Indonesian population, demonstrated strong reliability and validity through a combination of behavioral and neuroimaging data. The IFIS successfully captured the core cognitive processes associated with Gf, as evidenced by the activation of the frontoparietal network (FPN) during task performance. The study's multimodal approach, combining fMRI and EEG, provided a comprehensive view of the neural mechanisms underlying Gf and enabled accurate prediction of IFIS scores using machine learning techniques. The IFIS holds promise as a culture-fair tool for assessing Gf in Indonesia, addressing the limitations of existing Western-centric tests. The study's findings highlight the importance of considering cultural context in cognitive assessment and the potential of neuroimaging to validate cognitive measures. Future research can explore the cross-cultural application of the IFIS and its predictive validity for real-world outcomes, such as academic and professional success. Additionally, the multimodal approach employed in this study can serve as a model for developing and validating cognitive assessments for other diverse populations.

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