Stochastic Generative Image Model Contributes to sMRI Artistic Judgment Aptitude Validation

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Premise

This research describes instrumental role of artificially generated images during artistic judgment aptitude construct validation, then corroborates results with structural MRI brain scanning when hypothesis is an aptitude. MRI scanning shows artistic judgment aptitude is mediated by several aesthetic neuron networks with suggestion of asymmetrical lateralization to right hemisphere. Prominent questions addressed by this research are, first, do MRI brain scans support validity of stochastic generative images for artistic judgment aptitude testing? Secondly, how does generative art facilitate and enhance traditional cognitive test validation? Do generative algorithms and MRI affect construct validity? Finally, how might future research clarify other contributions of generative art to psychometric validation?

1. Introduction

Generative image algorithms have been developed for cognitive test models to assess verbal and spatial abilities in education and psychology [1, 2], but applications in aesthetics and visual arts, in general, are rare. Consequently, present research is first application of a generative algorithm to images presented during standardized artistic judgment (AJ) aptitude testing. This report describes contribution of generative art (GA) to AJ aptitude test development evaluated with structural magnetic resonance imaging (sMRI) technology. In this research, an AJ aptitude test model was first validated with conventional correlational procedures then investigated with sMRI brain scans.

Generative algorithms in psychometrics conveniently manipulate image properties such as complexity, redundancy, and spatial organization, which has implications for perception of order, coherence, and meaningfulness. These properties are sometimes referred to as syntax or formal design, and their manipulation fundamentally influences image preference. Generative algorithms can also produce images with affective properties independent of artistic style, image narrative, or thematic context. For example, serenity, agitation, confusion, harmony, and anticipation are affective properties that have been expressed by generative algorithms. Consequently, generative algorithms are very useful for experimental investigations that explore mental and personality development where control over image properties is important.

Not only can generative algorithms specify syntactical and affective properties in images, but specific properties can be replicated exactly without duplicating overall images. By imposing a stochastic procedure on the image algorithm, every generated iteration of an algorithmic specification can display intended formal structure while allowing overall image to vary randomly. Therefore, unique images with identical structural properties can be presented without creating boredom, fatigue, or concern that prior exposure will contaminate subsequent viewer responses.

Generative image algorithms do not affect traditional psychometric validation procedures, which require correlation between hypothetical construct and empirical criterion. In fact, generative algorithms improve construct development because specific image properties can be isolated and correlated with a criterion, which clarifies functional relations between properties and measurement target. Doing so, generative algorithms address a long standing problem in conventional test validation where aptitude constructs are commonly conflated with concurrent abilities and confounded with personality and socio-economic background. In other words, generative images provide more convincing evidence of validity than traditional correlation methods.

Purpose of this report is to describe neurological validation of a cognitive AJ test model that implements a generative algorithm to produce visual test images. Based on speculative aesthetic theory and empirical AJ studies, artificially generated images were first validated with professional artists using conventional correlational methods, then visual preferences and sMRI brain scans were collected from a layperson sample. Structural MRI results were correlated with AJ aptitude scores with intentions of identifying neuron sites that corroborate construct validity. For example, a sMRI scanning hypothesis was AJ aptitude is a measurable construct related to certain prominent neurological sites, as well as dedicated, neuro-aesthetic networks. In other words, high aptitude persons should show neurological structure that not only differs from those lower on the aptitude construct but is consistent with published studies of aesthetic appreciation.

Results in this research show AJ aptitude is mediated by a distributed neuron processing network and modest support for asymmetrical right hemispheric lateralization for at least certain aspects of AJ aptitude. In general, implementation of a generative art algorithm substantially improved AJ aptitude test validity by showing respective brain structures corresponding to independent test factors.

Prominent questions addressed by this research are, first, do sMRI brain scans support validity of generative images for AJ aptitude testing? Secondly, does sMRI validation, in fact, present implications for construct validity that significantly differ from traditional methods? A related question is, do generative algorithms and sMRI affect construct validity? Finally, how might generative art improve construct validation in future?

Sections below provide philosophical orientation to generative art, aptitudes, and mental measurement, which is followed by background for presented empirical research. Then structural sMRI results are presented of an AJ aptitude test sample. Validity implications of these results are interpreted for AJ aptitude testing.

1.1 Philosophical orientation

1.11 Generative art

From a broad metaphysical perspective, generative art is an insight into naturally occurring growth mechanisms found throughout nature. It is a cosmological principle that is not yet understood but is widely recognized. Dorin [3] below alludes to profound implications of generative mechanisms.

> Generative processes have been long evident in art, far predating current era of the digital computer. From Paleolithic ornamental art and hydraulically activated automata of ancient Alexandria (Hero 1st C. CE), Islamic art circa the ninth century, through to medieval and Renaissance clockwork figures . . . . all of these [have] generative processes. [3, p. 240])

Naturally occurring generative mechanisms are independent of particular artistic styles or movements and are, arguably, “universal” [4]. Philosophical foundations for these mechanisms are “Pythagorean concepts of unity and harmony based on numerical principles” [5]. They are fundamental to phylogenetic forces producing natural variation.

Mathematics and visual arts have long, extended relations, which promote contemporary statistical ideas about generative art. Pythagoreans, for example, predate Western philosophy, and their evaluation of proportions was instrumental to art and sculpture of ancient Egypt and Greece. Proportion in art has reappeared historically in Divine Proportion, Golden Mean, and Golden Ratio. By the Renaissance, painters were using mathematical techniques to achieve visual perspective, and a harmony between arts and mathematics continued through the Enlightenment. Nineteenth century cosmological confusion precipitated by thermodynamics and quantum theory provoked stochastic reactions in 20^{th} century art (Arps, 1917, *Collage with Squares Arranged according to the Laws of Chance*). Modern philosophers began to speculate on a scientific metaphysics defined by chance and probabilistic order [6].

Stochastic ideas echoed through 20^{th} century as contemporary artists absorbed underlying cosmological principles of chance and order. For example, Tzara and Arp were early promoters of Dada Art, which popularized chance in visual art. Kandinsky and Malevich would show its influence in their paintings. Mondrian and the school of neoplasticism were based on principles of chance and order. Drip paintings by Jackson Pollack and checkered paintings by Ellsworth Kelly both integrated stochastic methods in 1950s, while John Cage advanced autonomous stochastic procedures in visual arts in 1970s and 1980s.

The generative computational algorithm described in this report reproduces a mechanism of chance, order, and harmony commonly found in both nature and visual arts but with an adaptation that distinguishes between visual preferences of artists and nonartists. Order and complexity have been explicitly manipulated to separate visual preferences into aptitude-based differences predictive of artistic sensitivity.

1.12 Aptitudes

Aptitude conceptions were already contentious issues among philosophers in ancient Athens over 2,500 years ago. Aristotle presented a classical perspective in *Nicomachean Ethics* where aptitudes are natural capacities [7]. Like Plato, Aristotle equated political and philosophical abilities with natural endowments. In Plato's Republic, aptitude determines assignment to education and confers special social status. These rigid, exclusive ideas about aptitude changed during the Enlightenment when Kant [8] rejected fixed human abilities and asserted foundations for a priori mental structures now expressed in terms of "emergence", that is, knowledge that accumulates on basis of incremental experiences. Contemporary aptitude thinking leans toward epistemological conceptions that inherently depend on interactions between mental preconceptions (genetic aptitude) and learning, which establish knowledge. These ideas are foundations for developmental theory, yet archaic conceptions of aptitude as fixed mental traits remain dominant in lay discussions.

By the 20th century, classical rhetorical perspectives were replaced by ontological assertions that aptitudes are nonphysical, nonmaterial "entities" yet can be inferred by observations and are consistent with numerical representation. In context of Galton's broad eugenics movement [9], 20th century aptitudes became a psychometric invention thoroughly grounded in standardized testing movement of that time. Moreover, aptitude testing became instrumental to prediction of future student performance and integrated into public policy and college admission practices. Not surprisingly, college admissions board and scholastic aptitude tests were established in 1930s.

In contemporary discourse, aptitude has acquired objective statistical status and has gained prominence predicting human performance based on aggregated group parameters, while pseudo-scientific nomenclature has increasingly made aptitude conceptions less transparent. Aptitude has progressed from Platonic and Aristotelian rhetorical conceptions to contemporary developmental theory, which is filled with new terms such as latent structures, genetic variance, genetic factors, and genetic "influences" [10], as well as heritability estimates [11]. Aptitude is also generally subsumed under genetics of cognitive ability and behavior genetics. Aptitude in contemporary technical nomenclature is an obscure term to laypersons though typically associated with talent and ability. Not surprisingly, this shift to objective formulation is accompanied by growing politicization. By mid-20th century, aptitude was perceived as a source of socio-political control [12].

This shift from an Aristotelian rhetorical approach to contemporary statistical construct with predictive applications, however, is now recognized to come at substantial cost to human development. Traditional aptitude models have encouraged public policies that systematically exclude cultural minorities and disadvantaged youngsters from high quality educational resources, which, in turn, has institutionalized low school performance [17], as well as fostered an appraisal environment that discourages self-motivation and achievement [18, 19]. Issues surrounding debates between nativism and empiricism such as "emergence vs representation" models of encoding neurons,

relevance of latent structures and influence of social environment on human development are central to contemporary understanding of aptitudes.
As a biological concept, genetic traits govern broad areas of human development. Genetic determination of physical traits such as hair and eye color are commonly accepted, while many behavioral and psychological traits are also associated with genetic origins. For example, twin studies of behavioral traits and disorders such as aggression, schizophrenia, alcoholism, depression, and obesity now show significant portions of statistical variance associated with genetics [13].

Mental aptitudes such as music, language, mathematics ability, language, and visual arts also have genetic components. Substantial research has been conducted into genetics underlying music aptitude [14, 15]. Heritability estimates for creative arts-related aptitudes, which includes visual arts, have been estimated to range between .40 and .71, which suggest around 50 percent or so of observed variability can be safely attributed to heredity [11]. Not surprisingly, other research also points to central role of genetic aptitude in visual arts talent development [16]. Yet predictive accuracy is now understood to be precarious because aptitude expression is keenly dependent on genetic switches linked to both biological and social-cultural conditions.

2. Background

2.1 Generative image algorithms

Generative art in psychometrics has 19th century origins. A visual preference survey was first conducted by Fechner [20] when he manipulated proportions of an original painting to resolve an authenticity dispute. At that time, he pointed to central role of complexity or *variety* on visual arts preference and implied coherence or "unity" fundamental to understanding aesthetic preference. Fechner described procedures for measuring complexity of polygons but did not produce images.

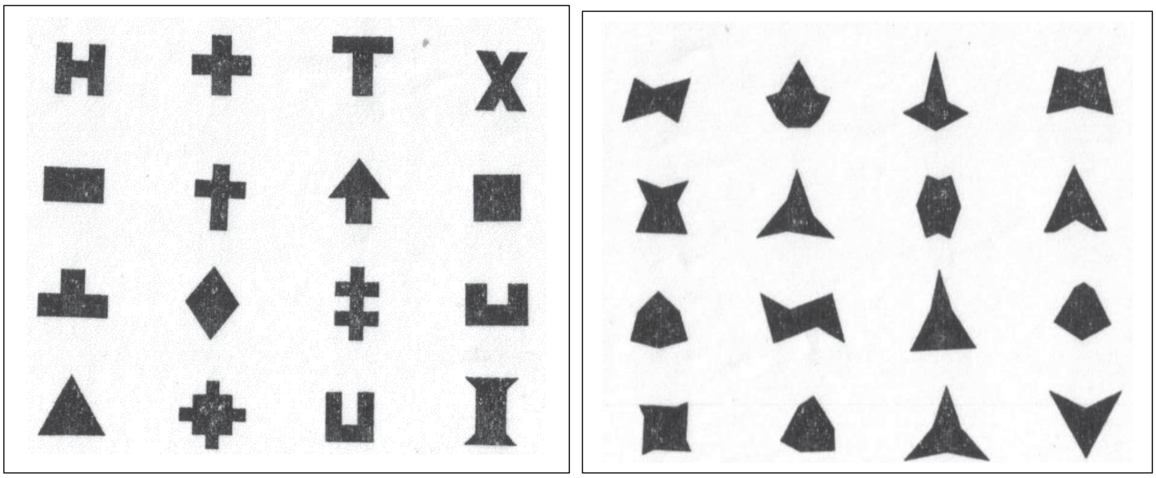


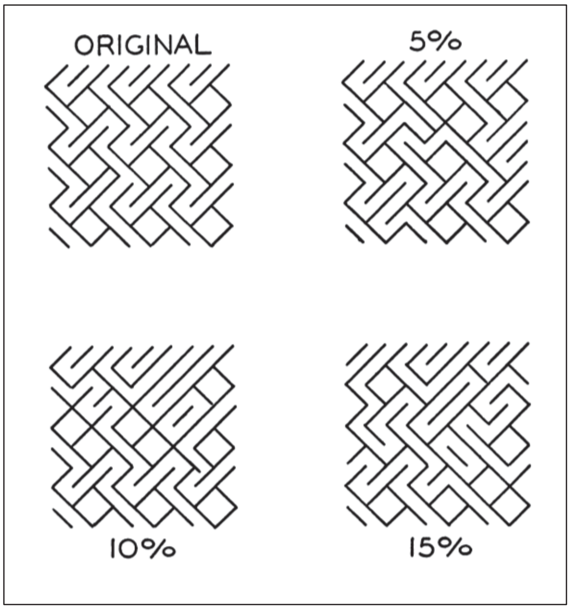
Figure 1. Birkhoff samples contrasting items with highest positive and highest negative factor loadings, from Eysenck [24].

Synthetic images representing explicit manipulation of complexity and order first appear in Birkhoff [21]. He proposed the following mathematical model and produced 90 polygons based on it.

$$M = O/C \tag{1}$$

Where M is an artistic measure that is a function of order and complexity. In other words, artistic value of any pattern is always greatest when order (O) is maximized relative to complexity (C). At any level of complexity, an increase in order always increases overall aesthetic value of a design.

Eysenck followed Birkhoff's lead and collected ratings for polygons from artists and nonartists, which he factor analyzed [22-25]. Figure 1 presents examples of Birkoff's polygons. Eysenck found those on left with highest positive factor loadings, while polygons on right with highest negative loadings. He combined them to obtain a "supra" factor with relatively high psychometric reliability, .89, which suggests visual preferences are quite stable, an extraordinary finding at that time. Eysenck empirically identified two visual preference factors, "T" and "K", and he considered T especially important because artists and nonartists agreed on it. A general preference factor, while K was a bipolar factor separating artists and nonartists. In general, he found



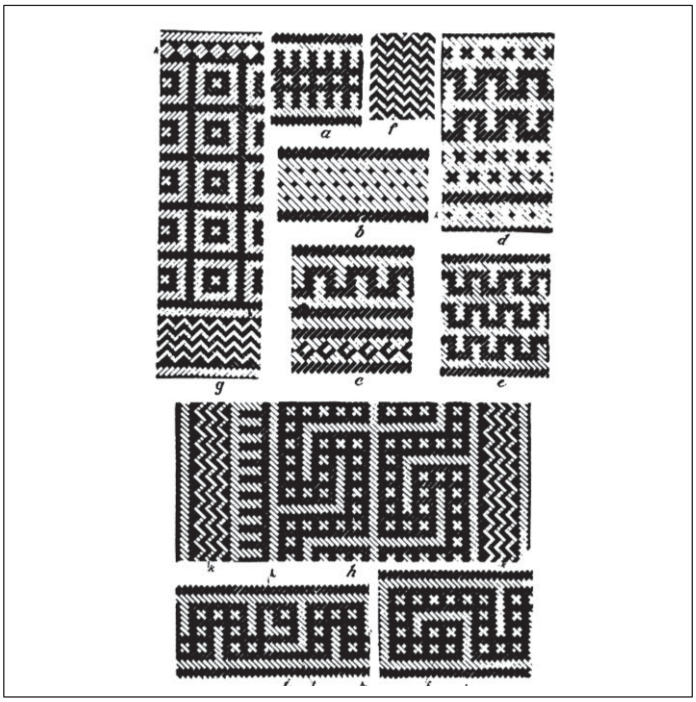


Figure 2. Attneave [30] discovers function of redundancy in visual images. His manipulation of redundancy on left demonstrates explicit visual effects. Image on right shows practical applications of redundancy in native basket weaving.

responses to polygons manifested a curvilinear relation between preference and complexity, which distinguished between nonartists and artists. Artists reach their peak for random complexity significantly sooner than nonartists. This important finding has led to enormous confusion because many replication studies failed to include both artists and nonartists, which lead to inconsistent and unusual results about preference for complexity. Eysenck's T later became basis for Visual Aesthetic Sensitivity Test (VAST) [26], which also became controversial because psychometric reliability was never adequate for valid use.

Eysenck successfully demonstrated visual preferences are consistent and a likely source of individual differences, which he speculated might be associated with personality [27]. However, his success was largely limited to preferences for polygons. Later, Attneave also conducted preference studies but in a format that we now call pixels [28]. Attneave [28-30] applied principles of information theory developed in acoustics to vision perception and discovered statistical parameters associated with preferences for statistical images that systematically differ in complexity and redundancy (order). Figure 2 presents several manipulations of redundancy and compares them with native basket weaving.

Attneave demonstrated effects of redundancy when manipulated as a fixed parameter. In contrast, Noll [32-34] advanced generative art by developing algorithms with fixed parameters which also included a stochastic component executed by computer. He essentially extended potential range of images and effectively introduced unique methods to produce images that simulated authentic visual art. Figure 3 presents computer rendered samples and a copy of Mondrian's *Composition with Lines*, 1917.

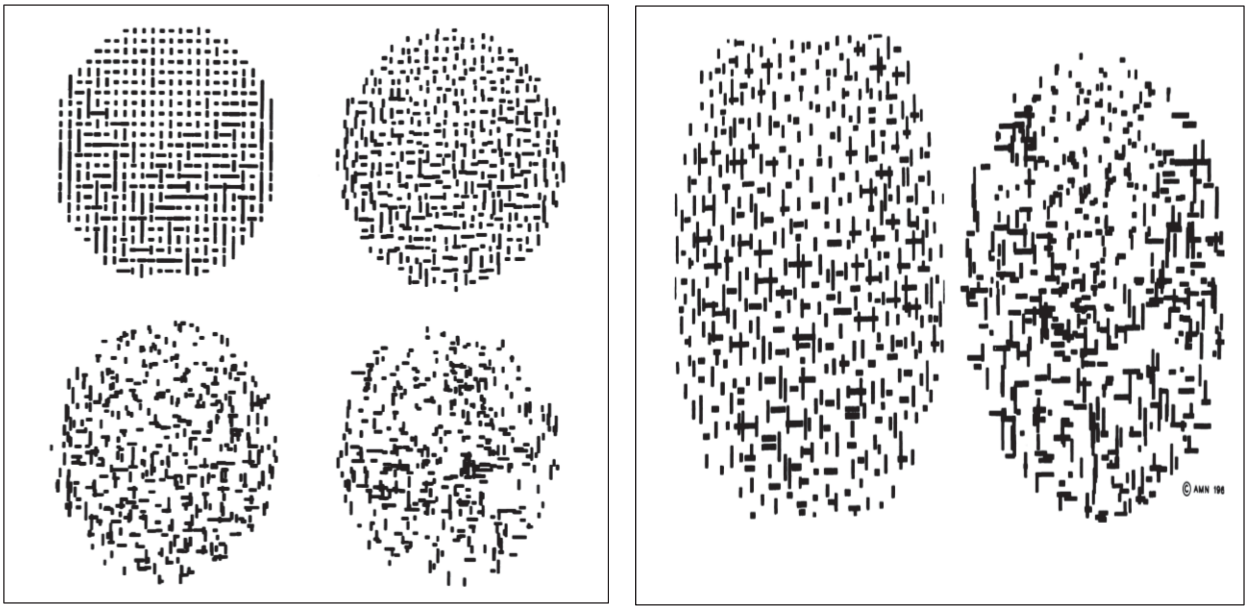


Figure 3. Images on left represent redundancy variations produced by computer [32]. Images on right compare Mondrian's Composition with Lines, 1917 and a computer reproduction.

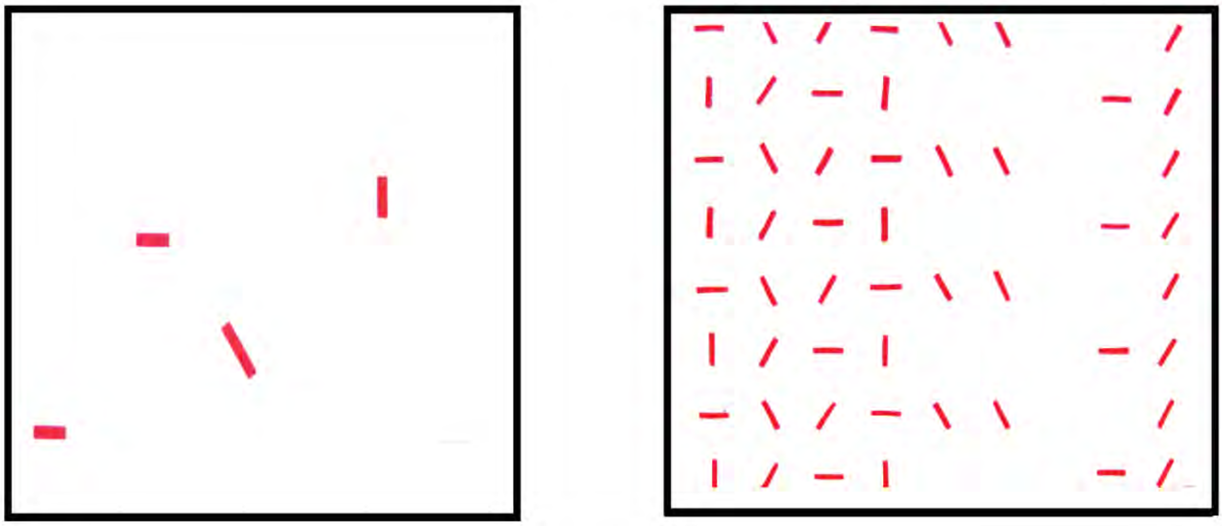


Figure 4. Generative image algorithm applied to aptitude measurement.

2.2 Generative art applied to AJ aptitude testing

Developments above describe key insights into stability of human visual preference, influence of image properties on visual preference, and image manipulation by computer algorithms. However, with exception of Eysenck, these advances did not address individual differences. A dedicated generative algorithm to produce images for identifying AJ aptitude differences first appears at the Johnson O'Connor Research Foundation (JOCRF) in Chicago in late 20th century when an effort was initiated to improve AJ aptitude testing.

Substantial advances described above made this goal reasonable and practical. Building on foundations of generative art and visual preference studies, a stochastic algorithm was developed to manipulate complexity and redundancy in random patterns, and factor analytic investigations confirmed Complexity and Redundancy factors. Extensive validation studies were conducted with adults and school children, as well as professional artists. Those studies found broad support for measuring AJ aptitude with calibrated test images. Figure 4 presents sample images from a generative algorithm based on Eysenck's K or complexity factor that distinguishes between artists and nonartists.

3. Generative art and test validity

Mental test development is dependent on items that solicit responses and empirical validation to establish meaningfulness of score distributions. Both requirements present special challenges to visual arts testing. Authentic, historical artworks are well-known and typically rich in thematic content, figurative details, and artistic style. Not surprisingly, these characteristics may interact with viewer background such as arts training and interest when images are presented for preference judgment. Consequently, AJ aptitude studies based on authentic artworks typically represent a confounding of genetic endowment, social-cultural background, and arts training. Despite protracted commercial and educational efforts through 20th century, failure to address these problems led to virtual abandonment of AJ aptitude testing. An exception is VAST, a standardized aesthetic sensitivity test originally developed by Eysenck based on his T factor. Unfortunately, field testing largely rejected VAST because of low score reliability and inadequate validation [34, 35]. Validation was based on a sample of only eight professional artists, while other research indicates confounding relations with personality, intelligence, and creativity [36].

In addition to complications presented by authentic art works, artist validation samples are also problematic because of vulnerability to selection bias especially in restricted small artist samples. See Osborne, [37] for discussion of artist validation problems.

GA addresses these problems in two ways. First, generative algorithms provide control over image production, which increases objectivity of aptitude testing. Images can be developed with specific properties such as hypothetical genetic components that can be separated from experience-based learning components during statistical analyses. Those image aspects believed to elicit genetic-linked responses can be isolated, while all other image properties are randomized hence eliminated from comparisons. Instead of idiosyncratic, subjective reactions to complex, multidimensional images, generative algorithms parse an image into those components directly relevant to cognitive or psychological performance being tested.

Secondly, generative algorithms provide an additional advantage by modeling AJ preference in a sequential process during overall image appraisal, which provides a theoretical context for collecting preference judgments and evaluating their validity. A related benefit is examination of separate factors during preference, which contributes to understanding perceptual mechanisms guiding preference judgments. Moreover, GA manipulation of separate factors facilitates evaluating their cumulative effect on preference, as well as interaction with other characteristics. Likewise, temporal effects of their presentation order become more apparent.

3.1 sMRI validation in psychometrics

In general, structural sMRI reveals neuron tissue associated with some aspect of person or environmental variation. Consequently, MRI technology offers a method of examining specific cognitive or affective structure and functions purported being assessed by a psychometric instrument, which is construct validity. For example, MRI has been applied to psychometric music and language aptitude models [38, 39]. Other examples are creative writing, which was divided into a generative and evaluative procedures and functional MRI mapping demonstrated separate activation pathways [40]. MRI has been useful for verifying cognitive change [41]. In present research, AJ aptitude scores were compared with brain tissue density and inferred brain function.

In this research, validity of GA images for measuring AJ aptitude was established first by conventional methods, that is, image properties were statistically correlated with preferences of a large sample of professional artists, which established a scoring protocol. When these images were presented to a sample of laypersons, structural MRI brain scans were collected and neurological gray matter density correlated with their AJ aptitude test scores. In other words, generative images helped to define a preference gradient or continuum, which was reconciled with visual preferences of professional artists. Then brain scans were collected of laypersons to verify neurological implications of validated aptitude scores.

A central issue in sMRI aptitude validation concerns hemispheric concentration of gray matter brain tissue. Traditional neurological views are visual arts aptitude should be lateralized to right hemisphere because of dependence on spatial abilities, mental imagery, and creativity [42], which contrasts with left lateralization of cognitive abilities such as math aptitude (addition and subtraction, left anterior portion of arcuate fasciculus [43], reading ability [44], cognitive abilities in general [45, 46], language (leftward lateralization of the inferior frontal gyrus in second language learners) [47], and music aptitude [48].

However, traditional ideas about hemispheric lateralization have been substantially weakened by growing sophistication of sMRI studies [49, 50], which emphasize more complicated neuro processing of creative arts distributed across both hemispheres depending on task. For example, Aziz-Zadeh et al. [51] found left lateralization even for canonical right hemisphere tasks, while drawing lateralization was not correlated with 22 variables in a study by McManus and Chamberlain [52]. Mihov et al. [53] did not find hemispheric differences in a study of creativity, while Bolwerk, et al. [54] did not report lateralization for visual arts. Moreover, direct sMRI evidence for hemispheric specialization during representative *drawing* is limited. Makuuchi, Kaminaga, and Sugishita [55] found drawing in nonartists characterized by bilateral parietal lobe activation, while Chamberlain et al. [49] presented mixed results in a drawing study. Following statement by Chatterjee and Vartanian [56] presents several contemporary issues concerning visual arts and hemispheric lateralization.

> The popular notion that the right hemisphere is the artistic hemisphere is likely wrong. According to this view, damage to the right hemisphere should profoundly affect artistic production and left hemisphere damage should largely spare such abilities. . . If anything, damage to the left hemisphere induced more extensive alterations in artistic production, including in the symbolism depicted, than did damage to the right hemisphere. [56]

Another issue in sMRI aptitude validation concerns whether aptitude brain structure conforms to published neuroaesthetic networks. Brown et al. [57], for example, conducted a comprehensive investigation of published neuro-networks and rejected claims they represent subsystems exclusively dedicated to neuroaesthetic processing. In contrast, Vartanian and Skov [58] concentrated on a narrower subset and identified a neuro-aesthetic network they believe more clearly defines a coherent neuoaesthetic system. The prominent issue here is whether aptitude-related neuron structure uniquely associated with professional artists replicates established neural-aesthetic networks. If aptitude results are mainly incoherent or inconsistent, then an aptitude validity argument is substantially weakened.

3.2 Hypotheses

An assertion in this research is GA methods for producing visual images can manipulate features that systematically elicit preferences associated with AJ aptitude. Moreover, this manipulation can target both physical and emotional properties independently of all other image features.

Given this context, goals of this research were to demonstrate convergence of preference for synthetic images with published arts-related neuro-processing centers. Then a related goal was to clarify whether neuron structure provides any support for asymmetrical lateralization traditionally associated with arts and creativity processing in right hemisphere.

Consequently, this research will test following hypotheses.

> Hypothesis 1: AJ aptitude is a physical entity. Therefore, sMRI brain scanning will identify significant gray matter density associated with AJ aptitude scores, as well as asymmetric lateralization to right hemisphere, the traditional center for aesthetic activities.
>
> Hypothesis 2: sMRI will demonstrate consistency between AJ aptitude structure and published visual arts processing networks, in particular, a neuro network established by Vartanian and Skov [58].

4. Method

4.1 Sample

Volunteers from Johnson O'Connor Research Foundation (JOCRF) in New York were invited to participate in an aptitude study, while sMRI scanning was conducted at Mt. Sinai Medical Center. All who volunteered were screened for medical and psychiatric illnesses including a history of head injury and substance abuse. The final 40 subjects completing sMRI included 21 males and 19 females, aged 18-35 years (mean age = 26.6, SD = 4.9).

4.2 Data

sMRI image parameterization was conducted with standard procedures.

4.3 Cognitive test model

Standardized test items (visual images) were constructed with a published statistical algorithm based on a theory-based visual arts test model and validated with

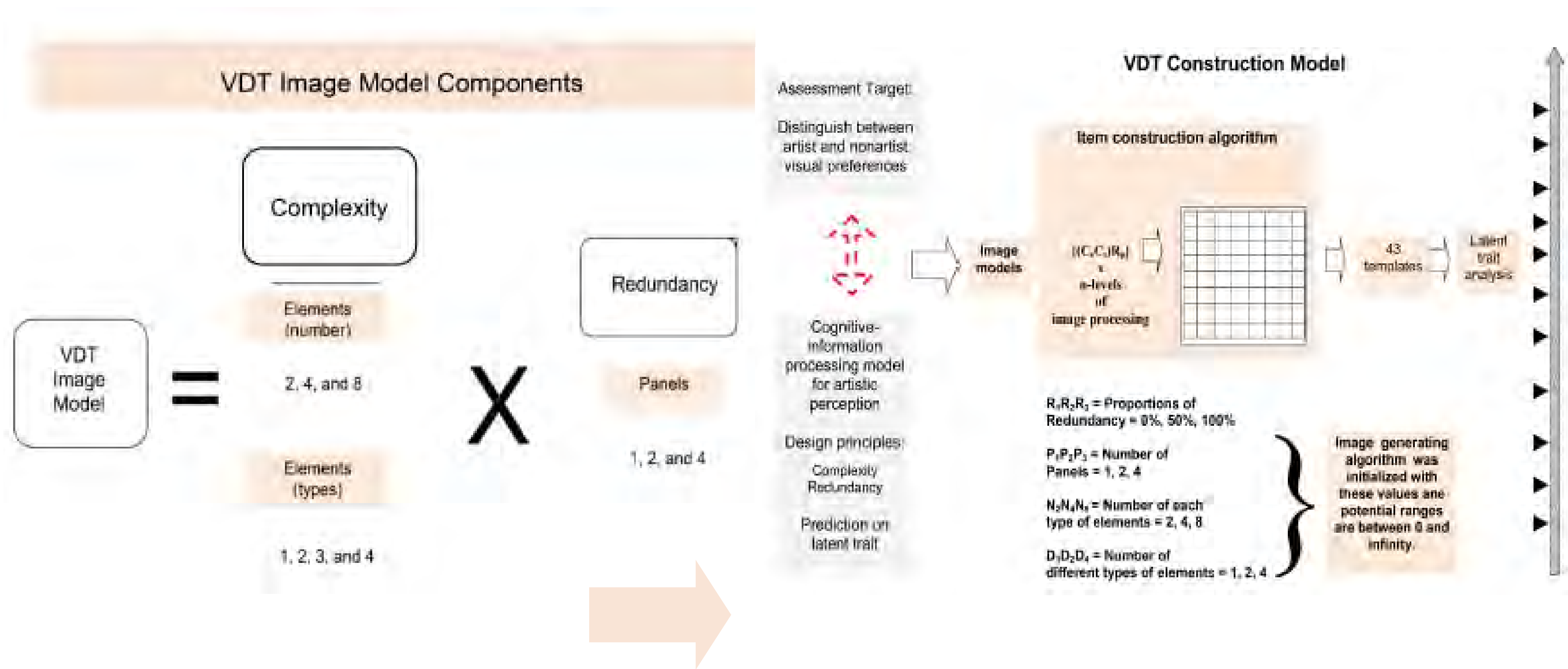


Figure 5. Synthetic image development with a statistical algorithm. Complexity and Redundancy factors were manipulated in random patterns based on a theoretical AJ cognitive-perceptual aptitude model where artists and nonartists significantly differ in visual sensitivity.

professional artists [35]. Item parameters were estimated with a linear probabilistic measurement model [59].

4.4 Psychometric image development

A cognitive model based on Eysenck's K factor, Attneave's stochastic composition process, and classical information theory principles [60, 61] was implemented to manipulate complexity and order (redundancy) in images that distinguish between artists and nonartists (see Figure 5). A factorial design was developed where 3 levels of 3 complexity factors were crossed with 3 levels of a redundancy factor to construct images contrasting higher and lower complexity/redundancy levels. Then 84 image pairs contrasting higher and lower complexity/redundancy combinations were presented to several JOCRF examinee office samples with instructions to select their preference. Their responses were dichotomously scored (0/1) in conformity with Eysenck's research indicating artists prefer less-complex designs. Conventional factor analysis then identified two prominent factors that were called Simplicity (Visual Designs 1) and Uniformity (Visual Designs 2). Original 84 items were reduced to 35 forced-choice items (Simplicity = 22 items and Uniformity = 13 items). Following algorithm represents an image model for simultaneously specifying complexity and redundancy in stochastic images:

$$(C_e C_t)R_p \qquad (2)$$

which was implemented across 1-layer of image processing levels, where each level has rank in an overall hierarchy, and: e = n of elements and n takes values 2, 4, and 8 t = types of elements and ranges from 1 to 4 p = n of panels p and n takes values from 1, 2, and 4, which leads to images of 0%, 50%, and 100% redundancy, respectively. Figure 3 presents complexity and redundancy components in a VDT image model.

Figure 6 presents an aptitude processing model that guided this research and distinguishes between artists and non-artists. Several principles underlie this model, namely, recursion, information components, and hierarchical order. VD 1 and VD 2 are processed by syntactic component early in the judgment process. Some authorities have demonstrated instantaneous decisions about artistic quality when images are presented. More complicated images would involve many more components and frequently several iterations through the model before an appraisal is established.

4.5 Analysis

Volumetric gray matter measurement/correlations were computed between scores and white matter density.

4.6 Procedures

Thirty five calibrated image pairs were printed and presented to several hundred examinees in JOCRF testing offices. Standardized protocol was followed and total test scores were entered in computer files.

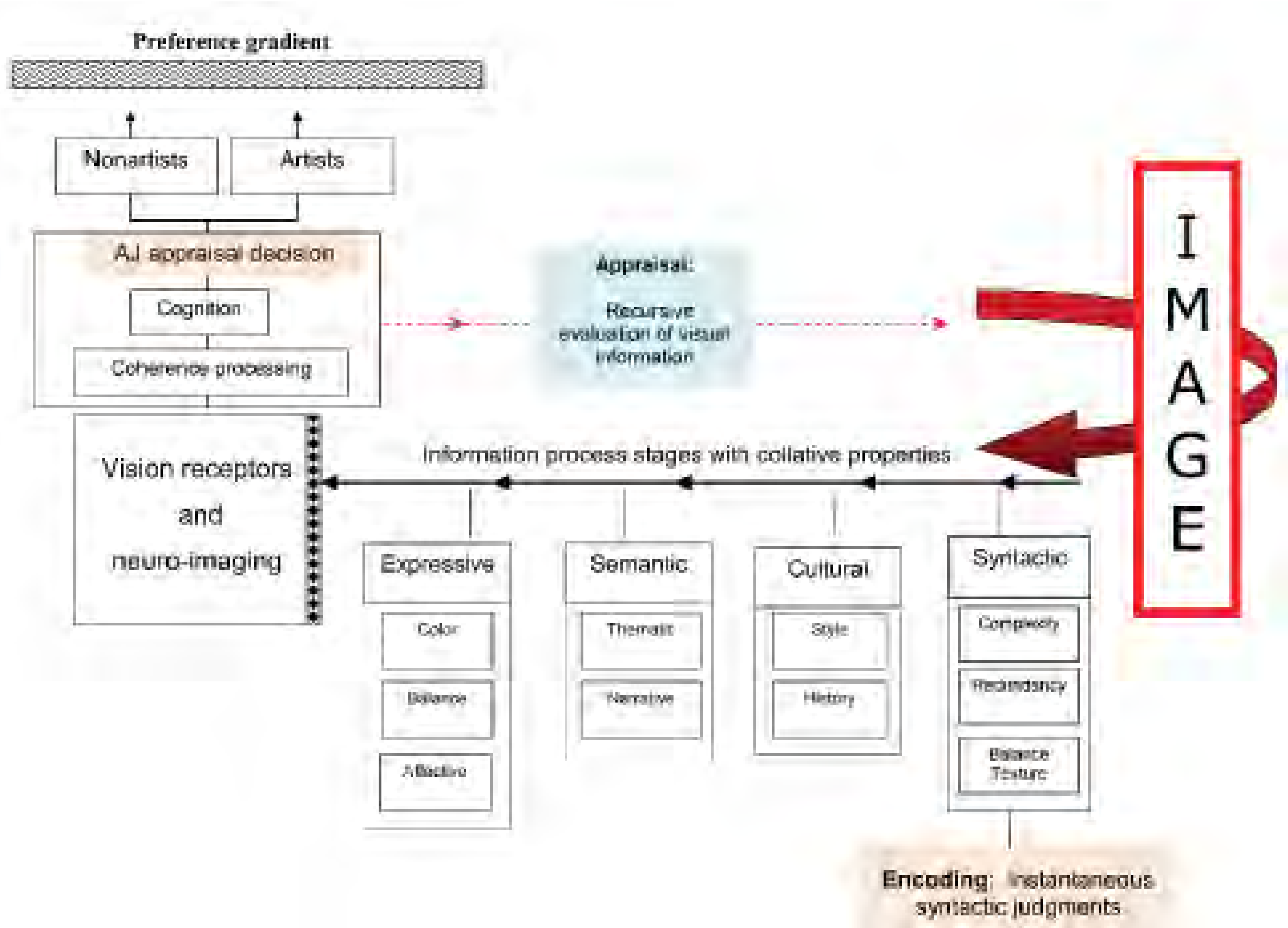
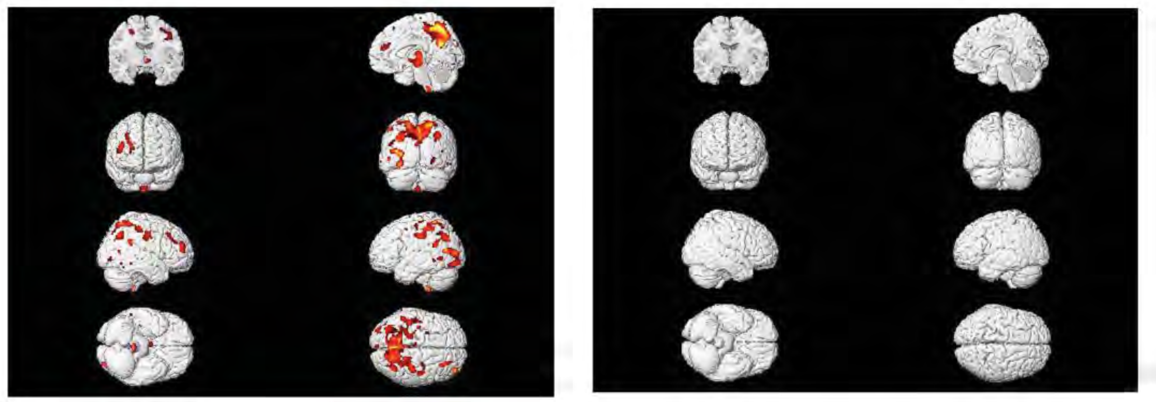


Figure 6. Information processing model of artistic judgment aptitude that distinguishes between artists and nonartists. This model implements multiple information components that are hierarchically organized and visually processed recursively. A viewer may circulate through visual information several cycles before arriving at comprehension and understanding.

Visual Designs 1

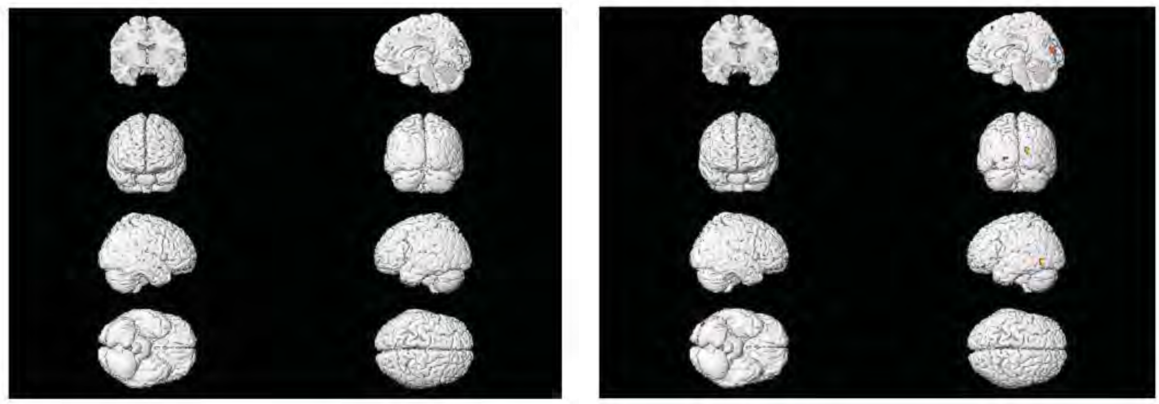
Overall

Positive Negative



Males

Positive Negative



Females

Positive Negative

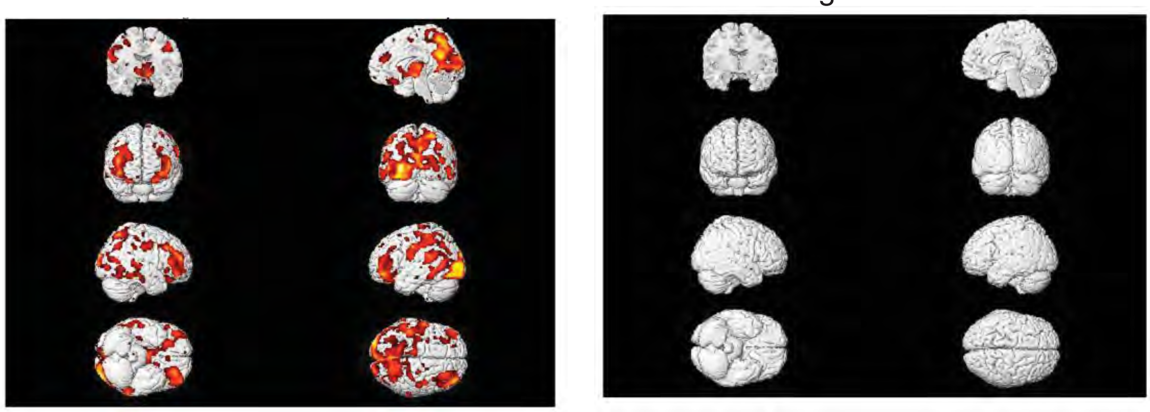


Figure 7. Distribution of increased gray matter density associated with VD 1.

Table 1

Brain regions in which gray matter density significantly correlated with Visual Designs 1 scores in overall sample (p < .01).

			Anatomy(Brodmann)		MNI coordinates			Cluster Size	Z	P_{uncorr}
					x	y	z			
VD 1										
Overall										
positive										
	R	Parietal lobe	Inferior parietal lobule	B 7	34	-58	42	257	3.81	.000
	R	Parietal lobe	Superior parietal lobule	B 7	16	-54	56	5349	3.73	.000
	L	Parietal lobe	Precuneus	B 7	-12	-46	54		3.46	.000
	L	Parietal lobe	Precuneus	B 39	-32	-64	35		3.42	.000
	R	Frontal lobe	Medial frontal gyrus	B 9	22	42	18	330	3.61	.000
	R	Frontal lobe	Middle frontal gyrus	B 8	32	27	37		2.77	.000
	R	Frontal lobe	Superior frontal gyrus	B 10	26	51	7		2.43	.008
	L	Occipital lobe	Middle occipital gyrus	B 19	-32	-83	13	695	3.53	.000
	L	Temporal lobe	Middle temporal gyrus	B 39	-38	-67	16		3.29	.001
	L	Occipital lobe	Inferior occipital gyrus	B 18	-34	-82	-6		3.04	.001
	R	Parietal lobe	Supramarginal gyrus	B 40	48	-41	30	130	3.31	.000
	R	Frontal lobe	Middle frontal gyrus	B 10	44	53	19	184	3.19	.001
	R	Brainstem	Medulla		4	-37	-45	158	3.09	.001
	R	Frontal lobe	Precentral gyrus	B 6	46	-14	34	255	3.06	.001
	R	Frontal lobe	Precentral gyrus	B 6	40	-4	33		2.52	.006
	R	Frontal lobe	Middle frontal gyrus	B 6	36	-4	46		2.44	.007
	R	Occipital lobe	Middle occipital gyrus		30	-76	4	74	2.98	.001
	R	Occipital lobe	Middle occipital gyrus	B 18	26	-82	-3		2.65	.004
	R	Brainstem	Midbrain	RN	2	-20	-7	615	2.96	.002
	R	Sub-lobar	Thalamus		4	-21	1		2.87	.002
	R	Sub-lobar	Thalamus	MDN	4	-19	10		2.69	.004
	L	Occipital lobe	Cuneus	B 19	0	-90	28	48	2.74	.003
	R	Occipital lobe	Middle temporal gyrus	B 19	40	-61	14	33	2.68	.004
	L	Temporal lobe	Middle temporal gyrus	B 37	-51	-58	1	43	2.68	.004
	L	Frontal lobe	Middle frontal gyrus	B 6	-24	2	44	66	2.67	.004
	R	Temporal lobe	Fusiform gyrus	B 37	40	-53	-11	23	2.48	.007
	L	Frontal lobe	Precentral gyrus	B 4	-36	-13	52	41	2.57	.005
	L	Occipital lobe	Lingual gyrus	B 18	-12	-68	2	26	2.60	.005

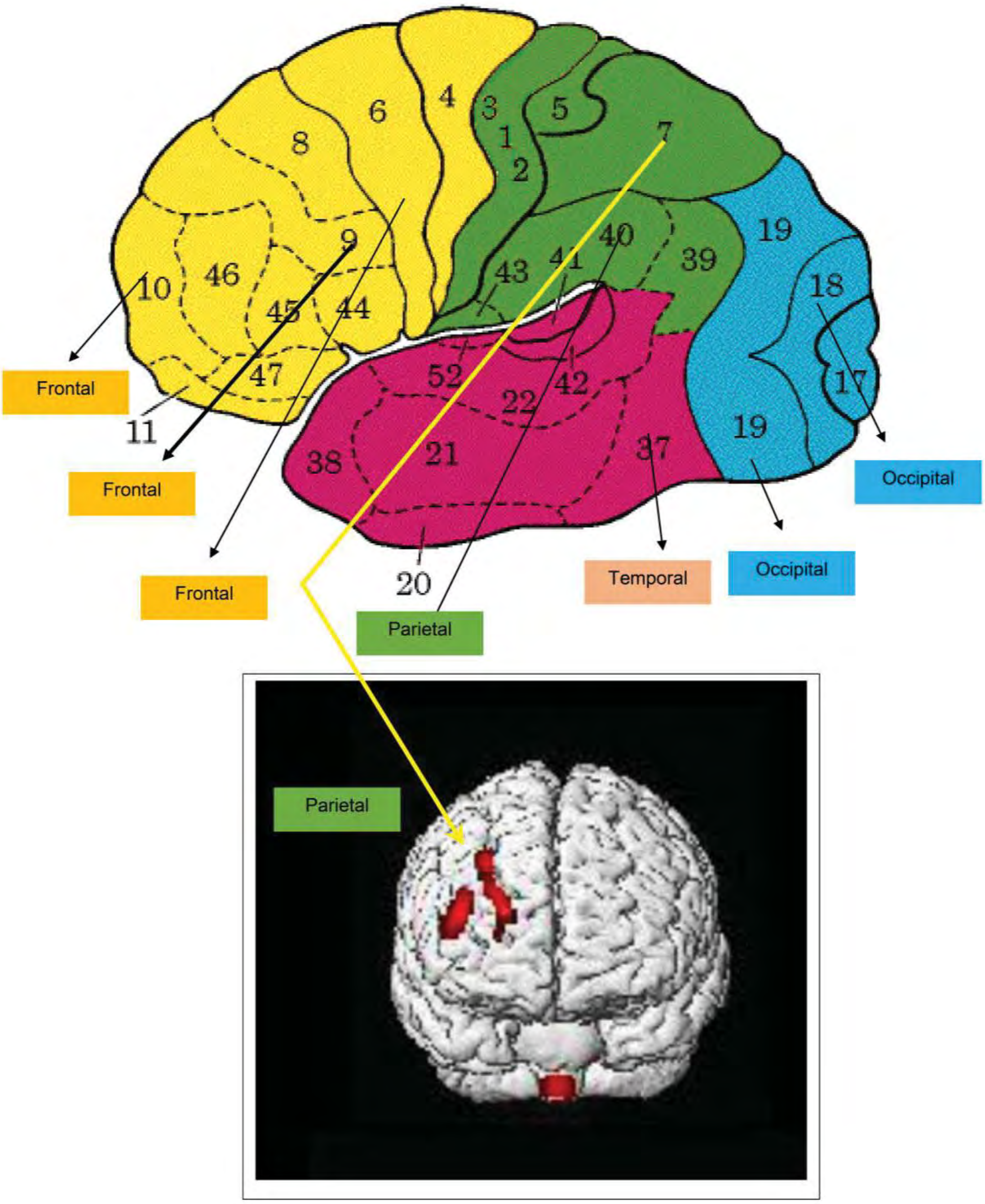


Figure 8. Brain sites show increase of gray matter density structure and asymmetrical lateralization to right hemisphere associated with artistic Judgment aptitude test scores.

4.7 Brain image acquisition and analyses (Structural sMRI acquisition)

A 3T Siemens Allegra sMRI scanner (Siemens Medical Systems, Ehrlangen, Germany) was used at Mt. Sinai Medical Center, NYC. (Scanning details on request.)

4.8 Voxel-based-morphometry and statistical analyses

Voxel-based-morphometry (VBM) was implemented to identify brain areas where gray matter volumes were correlated to AJ scores. Statistical Parametric Mapping software (SPM5; The Wellcome Department of Imaging Neuroscience, University College London) was implemented applying VBM unified segmentation protocol [62, 63].

5. Results

5.1 Overview

Data analyzed for this presentation show AJ aptitude scores were positively correlated with gray matter density in 21 brain regions spanning parietal, occipital, frontal and temporal lobes, as well as regions in the thalamus and brainstem. Figure 7 shows their distribution across brain sites, which indicates increased gray matter density of AJ aptitude is associated with following neurological functions:

- Visual processing (occipital lobe)
- Spatial relationships visual imagery (parietal lobe)
- Emotion (temporal lobe and insula)
- Dopamine (frontal lobe)

In addition, significant gray matter density increases were found in brainstem, both medulla and midbrain.

5.2 Aesthetic networks

Table 1 presents results identifying brain sites with significant correlations between matter density and AJ test scores. Results also show predominant concordance between AJ aptitude scores and specialized networks. For example, AJ aptitude scores were consistent with both passive, art appreciation neuro-networks [57, 58], and an active, representational drawing network [55].

5.3 Asymmetric lateralization

Finally, brain gray matter density showed both bilateral and asymmetrical lateralization with significant accumulation lateralized to right hemisphere. Greatest concentration of gray matter density occurred in superior and inferior parietal lobes of right hemisphere. Lateralization also occurred frontal, occipital, sub-lobar, and brainstem. Figure 8 presents graphic details about parietal lateralization and Table 1 presents coordinates.

6. Discussion

This study examined statistical relations between volumetric gray matter density and AJ aptitude scores based on visual preferences for images generated by a generative image algorithm. Images were presented in pairs that contrasted variations of complexity and redundancy. Prior studies had validated preference scoring with a broad consensus of professional artists. sMRI results showed significant correlations between visual preference, scored in direction of professional artists, and increased gray matter density in 21 brain regions. In general as AJ scores increased from low to high, gray matter density increased in those brain regions. Therefore, persons who tended to express preferences conforming to those of professional artists, tended to show increased gray matter density in corresponding brain sites, namely, frontal, parietal, temporal, and occipital lobes. Consistency between increased AJ density areas and published aesthetic appreciation networks was also evaluated for purposes of test validation, and those results showed general concordance of VD 1 and VD 2 with neuro-aesthetic networks.

As expected, results showed VD 1 (Complexity) and VD 2 (Redundancy) associated with different neuron sites, respectively, and VD 1 was dominant showing substantially more significant brain structure. Of that structure associated with VD 1, approximately 70 percent occurred in parietal and frontal lobes. As predicted, right hemisphere lateralization occurred primarily for VD 1 images.

6.1 GA contributions to test validation

While these results tend to support results from prior conventional validation procedures, GA implementation presented important epistemic benefits during sMRI, which substantially improved validation. Several benefits are described below.

- sMRI demonstrated a cognitive perceptual aptitude test model based on underlying factors is not only largely consistent with published neuroaesthetic studies of visual arts appreciation but also clarified the underlying perceptual mechanism – avoidance of higher complexity random patterns when presented in contrasting pairs.
- GA images provided insight into importance of coherence on arts-related visual preferences.
- sMRI results indicated that GA factors were instrumental to measuring not only visual arts sensitivity but also drawing production – an unexpected performance implication of AJ aptitude measured with VD 1 and VD 2.
- GA established foundations for constructing more complicated visual art and designing more sophisticated preference models.

Psychometric validation is a process of accumulating empirical evidence that supports claims of a test model. Those claims here refer to increased brain structure for high AJ aptitude persons, and consistency with expected neuro-processing. In general, these results show neuroscience analysis of preference for generative images offers insight into brain structure, as well as functions relevant to those claims.

6.2 Implications for cognitive test validation

sMRI brain scans provide physical corroboration for a hypothetical construct, which is more profound than validation with only conventional test score correlations. It offers insight into the cognitive mechanism involved in AJ aptitude expression, and in certain study designs, sMRI of GA preferences could provide values for estimating variance components of genetic and learned abilities. In this research, sMRI results also substantially expanded AJ aptitude interpretation by including drawing performance.

6.3 Future research

An interesting question is association of visual arts learning instead of AJ aptitude with brain structure, which may also show significant neuro structure. Bolwerk [54] in fact described substantial influence of art making on brain structure described below.

> We observed that the visual art production group showed greater spatial improvement in functional connectivity in frontal and parietal cortices . . . than the cognitive art evaluation group. Moreover, the functional connectivity in the visual art production group was related to psychological resilience (i.e., stress resistance) at T1. Our findings are the first to demonstrate the neural effects of visual art production on psychological resilience in adulthood. [54]

Other studies [40, 49] present additional support for neurological structure associated with visual arts-related learning. Consequently, results in this research would benefit from longitudinal study before and after visual arts training to clarify independence of aptitude neurological structure from experience and learning.

These prospective investigations of learning and aptitude, as well as neuroprocessing comparisons between professional artists and nonartists should be examined in the framework of linear measures. Published neuro-aesthetic studies are typically conducted with ordinal measures, which lack precision and objective measuring units for investigating longitudinal change.

6.31 More sophisticated visual images
Generative images examined in this research only manipulated complexity and redundancy at the syntactic level of image processing isolated from other information in an image. The algorithm developed in this research should be elaborated to accommodate more complex arrangements of hierarchical components with narrative, emotional and expressive content. These studies would lead to more sophisticated understanding of AJ aptitude brain structure.

6.4 Limitations

For an aptitude study, this research was limited by its concentration on a single observation of modest sample size. Consequently, variance components were not computed to clarify stability of neuro structures presented here. Another limitation was lack of professional artists in the sample. Some participants may have had some arts background, but without background information, association with neuro structures was not possible to investigate.

7. Conclusion

What are the contributions of GA to psychometric test validity?

- Isolation of relevant components in cognitive test model, which facilitates an understanding of their function during human performance.
- Theoretical cognitive foundations to guide construct development
- Reproducible methodology

How does sMRI improve mental test validation?

- Clarification of components that contribute to human performance
- Corroboration of cognitive test model theory with brain function and structure

Acknowledgements

AJ aptitude was examined in this research with calibrated stochastic visual images developed at Johnson O'Connor Research Foundation (JOCRF) for purpose of vocational guidance and is part of a larger JOCRF neuroscience commitment to aptitude testing advancement [64-67]. Author is grateful to JOCRF for sharing these data. sMRI scanning was conducted at the Mt. Sinai Medical Center, New York City and funded by the non-profit JOCRF. JOCRF did not exercise any institutional approval or supervisory role in preparation of the manuscript or decision to publish. Author thanks Chris Condon and Emily Eaves for invaluable help in data collection. Author appreciates expert contributions from Etienne Manderscheid and David H. Schroeder interpreting sMRI results reported here.

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