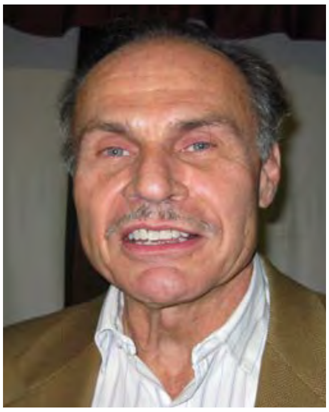
Nikolaus Bezruczko

Paper: **Generative art simplifies psychometrics of artistic judgment aptitude**



Topic: Generative art and psychometrics

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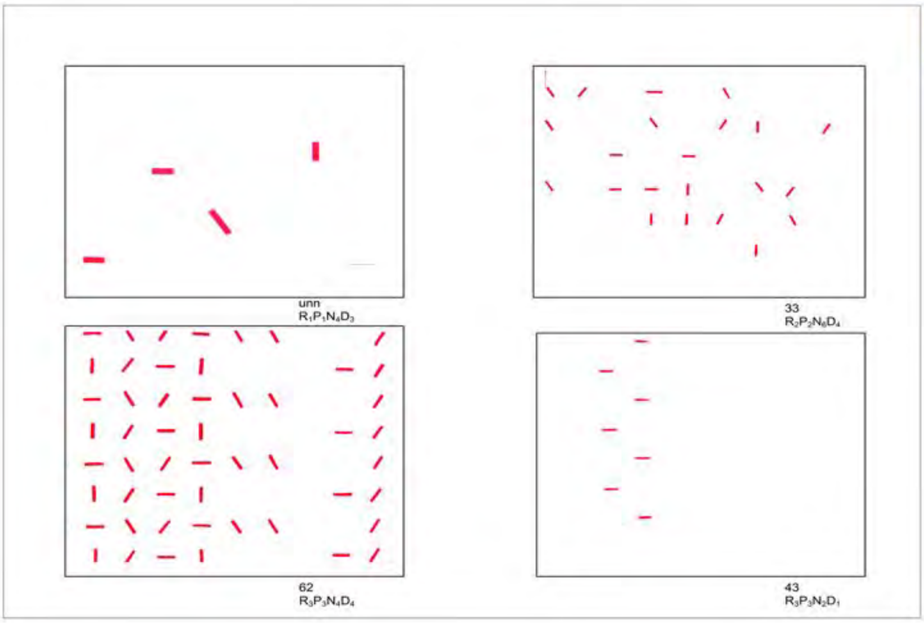
References:
[1] Fechner, *Vorschule der aesthetik.* Leipzig: Breitkopf , 1876.
[2] Birkhoff, *Aesthetic measure*. Cambridge: Harvard University Press, 1933.
[3] Attneave, Stochastic composition processes. *Journal of Aesthetics and art Criticism, 17*, 1959.
[4] Bezruczko and Schroeder, Artistic *Judgment III: Artist validation*, Technical Report , Chicago: Johnson O'Connor Research Foundation.
[5] Bezruczko, Measuring Artistic Judgment Aptitude, *Journal of Applied Measurement,* in press, 2013.

Abstract: Artistic judgment is widely appreciated across broad domains of Western civilization. Moreover, social researchers have studied its occurrence as aptitude for over 100 years. Unfortunately, complexities associated with objective images and validation has made artistic judgment aptitude measurement virtually intractable. This presentation will describe advances measuring artistic judgment aptitude using generative art. Many researchers have studied artistic judgment. Fechner [1] first conducted empirical studies in 19th century. Birkhoff [2] followed with mathematical studies and emphasized influence of order and complexity on artistic judgment preference. Other 20th century researchers investigated preference for controlled visual images and confirmed differences between artists and nonartists. Attneave's [3] research led to understanding that nonartists and artists fundamentally differ in sensitivity to redundancy (order). Present research continues contemporary empirical trend by demonstrating a stochastic algorithm that objectively manipulates order and complexity in visual images. Physical images were rendered in a Neoplastic style, and their effectiveness for measuring artistic judgment aptitude was validated with professional artists (*N* = 66) from several American cities [4]. This research will describe an artistic judgment information processing model, procedure for image production, collection of field observations, empirical analysis with a probabilistic Rasch model, and evidence for a psychometric construct. Finally, an algorithm developed at 1-layer will be generalized to n-layers of visual arts information. [5]



Images produced by a stochastic algorithm with generative properties. They have been psychometrically validated with professional artists and laypersons for measuring artistic judgment aptitude.

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Keywords: Artistic judgment aptitude, Rule based art, Automatic item generation, psychometrics, Rasch model

Generative Art Simplifies Psychometrics of Artistic Judgment Aptitude

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Abstract

An Important educational function in advanced Western economies is development of human talent both for efficient organizational management, as well as individual self-realization and personal satisfaction. Toward these goals, human aptitude measurement is instrumental to efficient use of rare human resources. Many cognitive capacities such as spatial, verbal, and intellectual reasoning are psychometrically evaluated, and their results have implications for pedagogy, career planning, and occupational counselling. Not surprisingly, artistic judgment aptitude is among those human capacities with both individual and cultural implications. Artistic expression to an important degree defines cultural development and is widely acknowledged to influence quality of life. Moreover, artistic expression contributes to perceptions of personal well-being, as well as transcendent states of spirituality and insight. Despite its enormous importance, artistic judgment aptitude measurement typically faces several challenges that have stymied practical development of objective measurement technology.

AJ aptitude measurement is problematic because theoretical knowledge is fragmented, literally scattered across more than a century of social research and most of it too fragmented for practical aptitude test development. Landmark 19th century studies established feasibility of inferring artistic judgment from visual preferences, and early 20th century researchers continued these studies. Dominant statistical factors that influence visual preference judgments were identified, and their relations to artistic judgment were investigated. However, practical artistic judgment aptitude measurement never became widely accepted nor supported by empirical validation studies.

A purpose of this report is to describe contribution of generative art methodology to improvement of artistic judgment aptitude measurement. A generative algorithm was developed that implemented statistical factors to produce visual images with explicit parameters capable of distinguishing between professional artists and nonartists. Developmental studies were also conducted to investigate aptitude origins of these preference differences. Application of generative art to image development addressed long standing objectivity and validity problems measuring artistic judgment aptitude.

An algorithmic information processing model was developed that manipulated syntactic complexity and redundancy in abstract images. Then empirical preference studies were conducted to examine differences between professional artists and nonartists. These results established both theoretical validity for an image construction model, as well as predictive validity of score implications. Then after several years of operational use, abstract generative images were followed by

production of controlled figurative images. In this report, brief historical background is presented of artistic judgment beginning with Fechner's 19th century landmark studies, then problems are summarized that plagued artistic judgment aptitude measurement for much of 20th century. Finally, a solution is presented that, first, models artistic judgment in a complex, sequential and recursive information processing structure. Then image decoding is isolated in the syntactic component of this model. Professional artists and nonartists are believed to process visual information differently, and an algorithm was developed to generate visual images that distinguish between them. Results are summarized in this report of empirical studies of these images.

1. Introduction

1.1 Philosophical orientation

Unlike traditional aesthetic studies, which strive for philosophical insight and understanding, artistic judgment (AJ) aptitude measurement is dedicated to practical humanistic goals with a prominent emphasis on objective, valid, and reproducible knowledge. AJ differs significantly from general aesthetic studies in social research by a conspicuous emphasis on professional artists and artistic values. Then this knowledge is implemented to solve practical issues of form, beauty, and function.

Visual arts are widely recognized to represent a humanistic accomplishment, and they typically define the civilization achieved by a people. Many commentators, for example, consider the arts and philosophy of ancient Greece to represent pinnacle of Western civilization. At a practical level, AJ is implemented every day in a broad range of activities and endeavours, and its prevalence tends to improve quality of life and personal states of being. Pervasive influence of AJ on practical affairs suggest aptitude research should present important benefits to students, teachers, counsellors, and parents. AJ aptitude, in fact, is instrumental toward success and productivity in many occupations and careers such as graphic arts, architecture, textiles, industrial design, cosmetology, dentistry, photography, and this list seems endless. Virtually any activity that requires visual appraisal is likely to benefit from AJ aptitude.

Unfortunately, objective AJ aptitude measures have been extraordinarily difficult to develop. Over 125 years of empirical AJ research has led to conceptual fragmentation and relatively minor consolidation of knowledge. Unlike most other aptitudes, artistic aptitude development and AJ in particular is closely associated with culture and social values, which is typically influenced by visual arts training and experience. This context for AJ complicates psychometric construct validation. A further obstacle to gaining practical knowledge about AJ aptitude is synthetic, controlled visual images are commonly rejected on artistic grounds. Consequently, scientific penetration of artistic phenomenon in general has been extraordinarily difficult.

Psychometrics emphasize statistical methods for identifying human mental capacities such as attitudes, opinions, achievement and ability, as well as broad range of mental aptitudes. Unlike traditional mental capacities, however, AJ aptitude presents special challenges in terms of construct development, artistic validation, as well as formulation of objective visual images that function as standard test items.

Conceptualization of AJ aptitude as a distinct entity subject to empirical relations can be traced to Eysenck's psychometric studies, which identified two prominent factors in visual preference judgments of artists and nonartists for geometric polygons [1]. Eysenck referred to them as "T" and "K". Eysenck conceptualized T as a general "taste" factor that describes sensitivity of laypersons to aesthetic differences that is trainable and related to education and arts experiences but with a substantial genetic component. Eysenck frequently compared T to an IQ factor in context of the arts.

The K factor differs from a common factor by distinguishing between professional artists and nonartists. Instead of representing a common construct, K represents fundamental *differences* between visual sensitivities of artists and laypersons. The K factor assumes AJ is a special talent not widely distributed among general population. A constellation of personality characteristics have been associated with artistic talent, and Eysenck went on to identify personality and aesthetic sensitivity of artists and nonartists [44]. A general goal since Eysenck's research has been to develop methods for identifying those persons with AJ talent, which has led to a hypothesis of a "latent trait" with explicit psychometric properties.

1.2 Generative art and psychometrics

Purpose of this report is to describe an implementation of generative art that simplifies AJ aptitude measurement by solving several problems associated with producing objective AJ images and their validation. A comprehensive review of the social research literature does not show another similar application of generative art to psychometrics. Therefore, advances reported here should be of interest to both artists and social researchers.

A basic conception in generative art is stochastic principles can release a visual image without direct manipulation of an artist [45]. Substantial advances in generative art are based on this idea, and this report describes its solution of following psychometric problems:

- Production of objective visual images independent of artistic intervention, which minimizes influence of style and arts background on visual preference.
- Inexpensive and convenient replication of visual images.
- Manipulation of image layers to probe fundamental perceptual process.
- Generative art frees art making from spontaneous inspiration of creative production.

Generative art provides capacity to examine discrete aspects of a very complicated process and manipulate those aspects relevant to some particular question. In doing so, generative art is clarifying the humanistic foundation of visual arts expression and emphasizing its implications for human affairs. In consequence, generative art has opened the door for future studies of AJ aptitude.

1.3 Aesthetic versus artistic judgment

Aesthetic studies address conceptions of beauty and their functions in human affairs, which contrast sharply with AJ aptitude emphasis on individual differences and practical, objective methods to identify these differences.

The term aesthetics is a broad concept that “encompasses the perception, production, and response to art, as well as interactions with objects and scenes that evoke an intense feeling, often of pleasure [2].” In contrast AJ is a complex neuropsychological capacity that differs across persons, yet is only one among several prominent aptitudes necessary for artistic productions.

Not surprisingly, differences between aesthetics and AJ have profound implications, which are summarized by the following:

- Historical antecedents differ significantly. Aesthetics has ancient philosophical origins. AJ arguably was initiated by Fechner’s 19th century studies followed by Eysenck's 20th century research.
- AJ is predominantly a practical matter of identifying a human difference.
- Aptitude emphasizes distinctions between artists and non-artists. Aesthetics tends to emphasize overall questions of beauty and “states of being”.
- Aptitude has much stronger emphasis on validity both as an artificial construct and subsequent interpretation of implications.
- Aptitude seeks to establish exact limits of knowledge and understanding.
- AJ aptitude is an explicit construction of scientific knowledge.

Narrow concentration of AJ aptitude on measurement of individual differences contrasts with broad, sweeping concerns of aesthetics on sensitivity and development, response and reaction, as well as expressiveness and communication. Aesthetics seeks an understanding of the sources of inspiration and crystallization of expression, while AJ emphasizes only objective human differences.

2. Scientific foundations: 19th and 20th centuries

2.1 Historical background

AJ preference studies have an unusually prominent history in modern social research. Beginning in 19th century, several empirical traditions including psychophysics, educational testing, psychobiology, information theory, and experimental psychology have examined AJ preference with controlled visual stimuli. Fechner [3, 4] first studied preference for Golden Section, which is a proportional aspect of visual preference prominent in visual arts theory since antiquity. Fechner's foundational work generalized Weber's earlier mathematical work with physical sensation and established a corresponding relationship between visual stimuli and subjective preferences. One consequence of Fechner’s advances is utilization of visual preference as indicative of perceptual processing, an empirical methodology that has become established in AJ research.

Birkhoff [5] conducted mathematical studies and concluded complexity and order are objective image properties that influence visual preference. He asserted AJ in particular occurs during a succession of discrete processing stages, a forerunner of contemporary information theory. In his model, complexity and order maintain functional relations with visual preference, and he proposed the model:

$$M = O/C$$

where M is an artistic measure that is a function of order and complexity. This means in any image, artistic value is always greatest when order is maximized relative to complexity. At any level of complexity, an increase in order will increase overall aesthetic value. Berkhoff 's algorithm for complexity and order remains a topic of interest among mathematical researchers [46].

Eysenck followed Birkhoff's work with extensive factor analytic studies of visual preference for polygons that found significant differences between artists and nonartists. Eysenck [1, 6] called the main factor “T”, a general Taste factor. Another factor that he called “K” is bipolar and distinguishes between artists and nonartists. Like Birkhoff, Eysenck identified complexity to be a key influence on visual preference. Control subjects expressed significantly higher preference for more complex polygons [7, 8]. Eysenck hypothesized fundamental genetic differences between artists and nonartists in visual perception, neurological function, and perceptual sensitivity. Unfortunately, Eysenck’s contributions were only based on ordinal score correlations and weak true score methods which ultimately would undermine his effort to measure artistic judgment. In fact, a test derived from Eysenck’s T, the Visual Aesthetic Sensitivity Test (VAST), tends to be unreliable [9, 10].

Finally, Berlyne [11, 12] extended idea of information processing stages and proposed several levels, namely, syntactic, semantic, expressive, and cultural that convey artistic information. Although empirical studies have not yet demonstrated information extraction from these stages, complex art likely requires sequential, as well as recursive processing before arts-related cognition concludes. Berlyne's emphasis on syntactic information would have special importance for contemporary advances. Syntactic information involves physical configuration of visual elements in an object or pattern and is fundamentally related to balance and layout design.

Social researchers have shown an enduring interest in Berlyne’s research because he found image complexity to follow a curvilinear preference function. He reported visual preference for image complexity monotonically increases until reaching a maximum, and then preference steadily declines. Unfortunately, his studies did not include professional artists, and social researchers incorrectly concluded that preference for complexity indicates higher AJ. Contemporary social researchers, in fact, are surprised to learn that Berlyne’s complexity function is *inversely* to related AJ, when samples include professional artists. In fact, complexity affects professional artists and nonartists differently. Inadequate sampling and overgeneralization of results has led to confusion concerning complexity and AJ that continues to muddle empirical aesthetic research. Martindale commented extensively on confusion and inconsistency surrounding Berlyne’s research [13].

Fechner, Birkoff, and Eysenck are largely unappreciated in social research for an innovative line of inquiry that established a new way of looking at subjective experiences. They challenged historical conflicts between traditional physical science and social research and demonstrated perceptual preferences, subjective appraisals, and statistical order can lead to empirical knowledge. These accomplishments now establish a foundation for virtually all significant empirical work measuring AJ aptitude. Their advances, arguably, have established a standard for all social research and provides an important perspective on future studies.

3. Contemporary research

3.1 Stochastic image models

Twentieth century progress toward measuring AJ was substantial but incomplete because following problems could not be solved.

- Uncontrolled influences on visual preference contaminated AJ aptitude measurement.
- Artistic quality of controlled images for AJ aptitude testing was unacceptable.
- Test validation was inadequate because aptitude researchers neglected to distinguish between artists and nonartists.

Two significant advances facilitated implementation of generative art in AJ aptitude measurement. First, Attneave [14, 15, 16] described role of complexity and redundancy on visual preference, and speculated artists have highly sensitized visual receptors that may be easily stimulated by subtle redundancy features in complex patterns. He speculated nonartists may be less sensitive to redundancy and less able to simplify complex fields. Consequently, his research led to speculation that a discriminative perceptual mechanism distinguishes between artists and nonartists. Second major development was Noll’s computer demonstration that generative art could have strong aesthetic properties [17, 18]. Noll was first American to apply computer technology to construct objective visual images, which led to broader mainstream recognition of stochastic influences on visual art.

3.2 Information theory and perceptual models

Visual stimuli consist of many information sources that in some cumulative manner influence visual preference [11, 12]. Viewers are believed to extract information during image scanning and relay it to specialized neuron receptors where neurological processing reassembles a meaningful gestalt or percept. A key mechanism in this process is image decomposition and information extraction. Information theory proposes extraction is governed by several principles such as uncertainty, amount of information, organization, and coherence. In simplest model, Platt [19] proposed separating aesthetic information into formal and stylistic information levels, while Moles [20] proposed a more complex system that simultaneously superimposes qualitatively independent information levels on an image during perception. He emphasized that "each level conveys its own unique message and possesses specific rules of organization" [20, p. 474]. Moles advanced conceptual foundations further by proposing a hierarchical information processing system in which artistic perception is decomposed into independent qualitative levels then reconstructed during cognition. Perceptual sensitivity and capacity are key differences he proposed between artists and nonartists. He emphasized prominence of semantic information represented by cultural conditions such as religion or government on visual preference. Finally, Berlyne proposed expressive and syntactic levels [11, 12], during perceptual processing. Expressive level transmits some personal aspect of artist, while syntactic information is physical configuration of visual elements in an object or pattern. Influence of this approach can be found in contemporary research [21, 22, 23].

3.3 Professional artists, contemporary art, and perceptual models

Interest in role of chance on image production was not restricted to 19th and 20th century science and technology. Professional artists since Picasso have been deconstructing visual images, and Mondrian emphasized structural organization of paintings without explicit figurative content. "De Stijl" and neoplasticism were an early 20th century art movement dedicated to foundational aesthetic principles [24]. Figure 1 presents several 20th century examples of 20th century contemporary art that integrated random principles into their production. By 1950s, professional artists such as Kelly were explicitly implementing stochastic mechanisms in visual art. For example, in *Spectrum Colors Arranged by Chance I to VIII*, Kelly, an American artist, completed a series of collages by using numbered slips of paper, which were indexed with specific colors. He then used one of eighteen different hues, which were randomly assigned to locations on a grid 40 inches by 40 inches. Moreover, he used a different stochastic process in each of eight collages. Kelly appears to have been first professional artist to implement probabilistic modes systematically in art.

Kazimir Malevich, *Eight Red Rectangles*, 1915

Theo van Doesburg, *Composition VII (The Three Graces)* 1917

Ellsworth Kelly, *Arranged by Chance*, 1951

Ellsworth Kelly, *Spectrum Colors Red and White*, 1952

Figure 1. Ellsworth Kelly used numbered slips of paper, which were assigned by chance to a grid pattern in his paintings.

3.4 Problems and challenges

While substantial 19th and 20th century knowledge accumulated about AJ, aptitude testing remained relatively primitive because AJ is both a shared, cultural experience, as well as genetic aptitude expression. Not surprisingly, intensity of this interdependency stymied virtually all efforts to separate AJ into objective and subjective aspects. Not until 1980s, when Johnson O'Connor Research Foundation (JOCRF) undertook a major initiative to develop an AJ construct for occupational and vocational counselling was an algorithm developed to construct objective images. JOCRF's strategy was to diminish costs of traditionally painted artwork and improve predictive validity by developing an objective image model based on information theory. Then a generative algorithm was developed to produce test images. Definitive validation by professional artists followed, which rationalized test design and image template development.

AJ aptitude measurement has faced stubborn challenges. For example, close relations between artistic judgment and social context undermine objectivity necessary for valid measurement. Other problems included generally weak artistic judgment criteria, as well as inadequate validation samples. In general, synthetic images were typically rejected on artistic grounds.

Theoretical fragmentation also inhibited AJ aptitude measurement. For example, AJ image processing is complex, and even simple images present an enormous amount of information to viewers. Early interest in proportions, then investigations of image characteristics, that influence visual preference, and emergence of information processing theories have not led to theoretical consolidation. Consolidation of AJ research across traditional disciplines (psychology, cognitive science, information processing, and experimental psychology), as well as more recent neuro-imaging studies has not occurred. Not surprisingly, fragmented and incommensurable conceptual perspectives, as well as inconsistent empirical interpretations has inhibited coherent AJ construct development.

3.5 Contemporary AJ aptitude testing

AJ aptitude testing with generative test images is currently conducted in JOCRF testing offices, which is located in several American urban centers. JOCRF has been developing aptitude tests since 1920s and is the largest aptitude testing organization in USA. Until 1980s, JOCRF based AJ testing upon visual appraisal of stimuli with controlled proportions, which was never widely endorsed within JOCRF nor by professional artists in general. Consequently, JOCRF undertook a major initiative to develop a new AJ test construct based on contemporary scientific knowledge of AJ perceptual processing, stochastic generative models, and visual arts theory. Visual Designs Test (VDT) is a product of this research and an example of generative art implementation, which substantially improved AJ aptitude measurement [25].

4. AJ aptitude measurement theory

4.1 AJ construct

First, AJ needed a plausible but comprehensive aptitude construct with hereditary antecedents that interact with experience and education. Then some aspect of overt human behavior needed to be identified that reveals AJ aptitude and is related to a wide range of artistic activities. These considerations led to a construct based on visual preference for “physical elements organized in space”. Visual preference is logically fundamental to all artistic expression and both visual preferences and spatial abilities are linked to substantial prior AJ research. An emphasis on preference also simplifies the immense complexity of AJ by excluding physical production, appreciation, and training. The following sections describe a preference construct that was elaborated by advances in contemporary behavioral science.

Twentieth century information theory and experimental aesthetics provided a theoretical context for hypothesizing AJ as a specialized cognitive processing aptitude. This fundamentally new approach to AJ aptitude exploited following principles about human perception, aesthetic preference, and physical objects:

1. Artistic judgment is based on systematic perceptual processes. Humans, for example, implement a scanning process that decomposes visual stimulation into discrete information levels, and then simultaneously reconstructs them into personally relevant meaning. This process is sensitive to feature attributes such as contours, colors, textures, and complexity, which interact with experience and knowledge, as well as linguistic and conceptual cues.

2. Objects and patterns have objective properties that are independent of human perception and a basis for their artistic valuation. These properties conform to physical laws and have psychological effects that are expected to remain stable and consistent over time.

3. Neurological sensitivity to visual information varies among persons and is largely innate. Persons with artistic aptitude are expected to be more sensitive to visual stimulation. Innate sensitivity differences to arts-related stimulation between artists and nonartists are the foundation for an aptitude approach to AJ.

4. Given a visual choice between meaningless alternatives, artists prefer less-complex designs. (Artist preference between meaningful alternatives is profoundly more difficult to describe.) Moreover, preference for less-complex designs also appears to have stable aptitude properties [8, 26]. Other physical features that distinguish artists from nonartists such as symmetry, balance, and proportion, as well as information properties such as novelty, interestingness, and pleasingness appear mediated by culture and socioeconomic status [8].

4.2 AJ processing model

A provisional AJ perceptual processing model was formulated for this research to guide theory development and instrument construction, which is presented briefly below. AJ preference was hypothetically modelled in an information processing structure divided in several stages that were defined by specific extractions of syntactic, semantic, stylistic, and expressive information. This model revisited theoretical considerations initially proposed by Berlyne [11], but integrated insights from contemporary perspectives [21, 22]. Unfortunately, these contemporary models tend to emphasize aesthetic aspects not immediately relevant to practical aptitude measurement. Moreover, contemporary aesthetic processing models are not generally validated by both nonartists and professional artists, which limits their usefulness for aptitude measurement. Consequently, an artistic judgment processing model was specifically developed for present research that emphasized differences between artists and nonartists, which is presented in Figure 2.

Figure 2 presents an overall perceptual processing structure of components and stages developed specifically for AJ measurement [43]. Image processing in this structure involves decomposition into memory registers, recursive separation of visual information into cognitive and affective components, and a stage of critical evaluation and artistic judgment. This process then enters a stage of image reconstitution mediated by personal affect, which concludes in an overall cognitive judgment concerning meaning and comprehension. Simultaneous with overall processing is dynamic within image processing that emphasizes collative image properties such as complexity and redundancy, which distinguish between professional artists and nonartists. While comprehensive artistic cognition is deliberative and recursive, contemporary studies agree preference for complexity occurs almost instantly during initial encoding [27, 28]. In other words, syntactic structure of images is specifically isolated in this processing model, and preference values are assigned very early independent of overall information saturation of any given image.

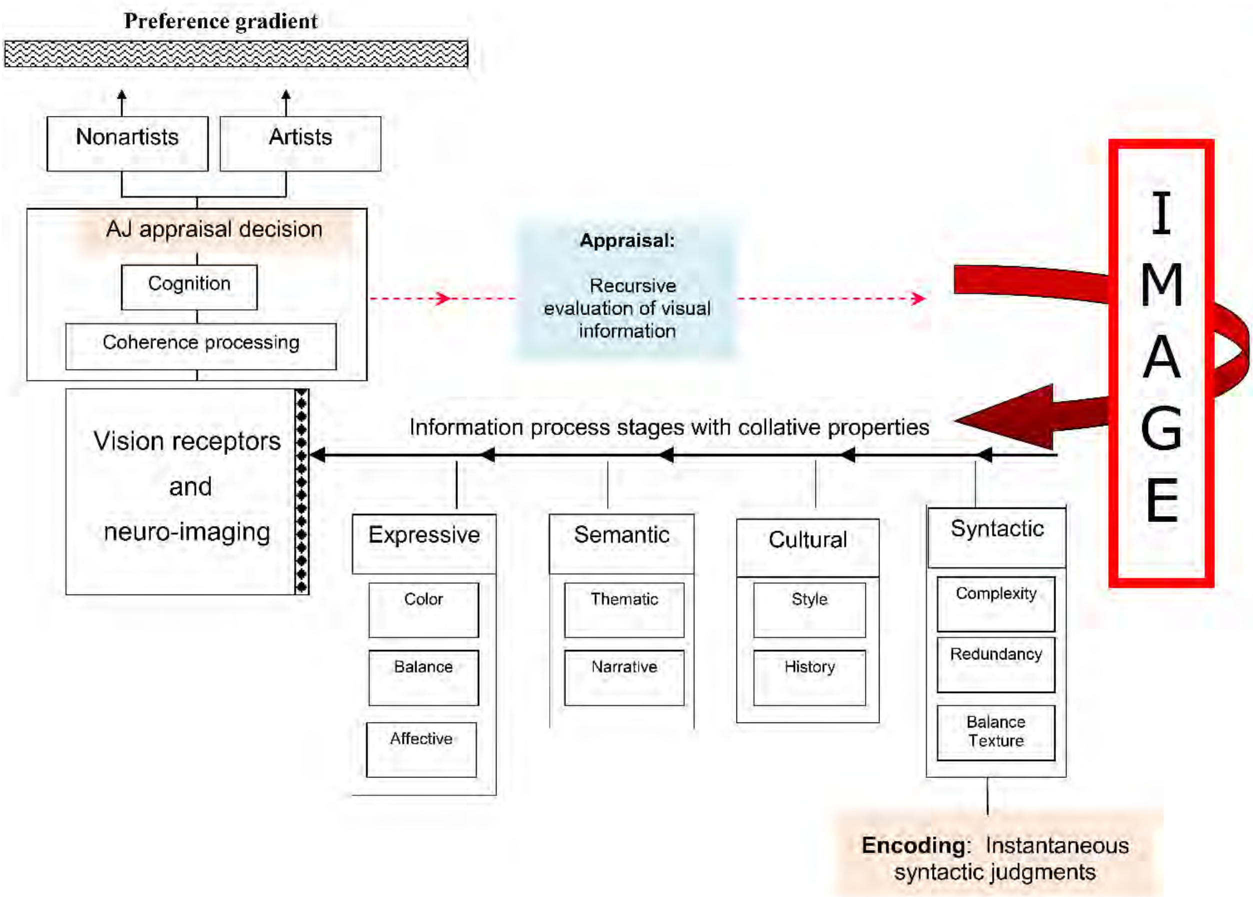


Figure 2. Information processing model of artistic judgment

According to this aptitude model, artistic perceptual sensitivity should lead artists to be less tolerant of complex images with low structure (high complexity and low redundancy, which are images consisting mainly of random visual noise. Consistent with empirical research, artists will prefer less preference for random complexity than nonartists. Likewise, artists should express higher preference for complex, coherent, syntactically balanced visual images independent of meaningfulness.

5.0 AJ image development

5.1 AJ test design strategy

An AJ aptitude test goal was to establish an objective visual preference gradient based on images that systematically varied along theoretically significant design features. These design features should distinguish between visual preferences of artists and nonartists. To reach this goal, a research plan was developed that a) hypothesized an empirical AJ visual preference model based on published research, b) formulated a strategy to isolate visual preference judgments, then, c) developed a theoretical construct amenable to practical implementation. In this context, an image construction model was developed to manipulate images that would separate artists and nonartists on a visual preference gradient.

Following sections describe empirical AJ methodology that was implemented.

- isolation of syntactic attributes in visual images
- operational definition of complexity and redundancy with an objective, rule-based algorithm
- statistical manipulation of complexity and redundancy in image models
- collection of visual preferences from professional artists
- adaptation of image model specifications for figurative images

5.2 AJ image components

Prior studies had identified complexity and redundancy as "radical" influences on item difficulty, which should influence visual preference. Neurological sensitivity has long been considered instrumental to significant preference differences between artists and nonartists [16]. These principles were represented in an image model by operationally defining both complexity and redundancy in the following algorithm:

$$(C_e C_t) R_p$$

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.

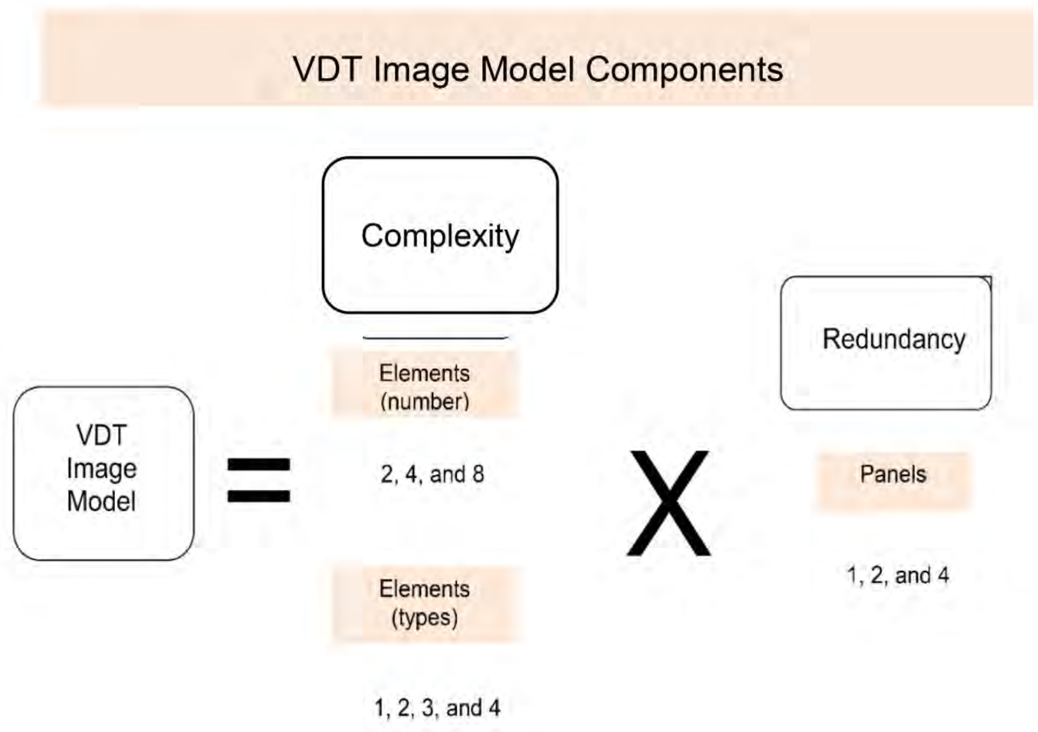


Figure 3. VDT image model components

5.3 Objective test images

Separating cultural, stylistic, and historical criteria that influence AJ has been a long standing obstacle to social researchers. A related problem was establishing an objective artistic standard for evaluating personal visual preferences. Complicating psychometric test development, AJ is emphasized in visual arts education and professional training, which contaminates validation procedures. In addition, a common perception of laypersons is visual arts function outside scientific boundaries hence AJ testing is impossible to conduct [29, 30]. Consequently, empirical studies that purport to be objective about AJ tend to raise profound suspicions among artists, and altogether, these conditions fundamentally undermine conventional validation procedures. While talent is widely associated with AJ, forces described above largely prevented aptitude testing advances for most of 20th century.

Generative art played an instrumental role in breaking through methodological impasse of AJ aptitude testing. An algorithm for producing objective images virtually eliminated influence of arts training and background on visual preference. This image model manipulated key predictors of visual preference, which was coded in image templates, which then were field tested. Moreover, this image model was based on theoretical principles, which provided strong support for construct validity. These images were also broadly endorsed by a substantial sample of professional artists, and validation studies distinguished between artists and nonartists [36].

Development of a response mechanism was initially problematic. A response mechanism represents that aspect of human behaviour related to target performance. Mental ability testing in general emphasizes human performance in an educational or training context because a purpose of mental testing is to assess effectiveness of that training. Unfortunately, traditional approaches to ability and achievement contextualized by training and education weakens validity foundations for aptitude measurement. In contrast, AJ aptitude testing emphasizes instrumental role of a “latent trait” on human behaviour independent of education or training context but necessary for successful occupational or professional performance. In other words, an AJ aptitude test does not infer what examinees can do artistically, but rather their visual inclinations independent of training. In fact, visual preferences are typically considered an expression of personal taste and presumably less dependent on formal education or art training.

5.4 Image template construction

VDT test model consists of a single image model, which is defined by a range of complexity and redundancy attribute values. Any generated template is only a “snapshot” of image possibilities and has virtual capacity to generate images limited only by physical constraints. Several procedural steps were completed to produce images. First, a physical cell structure was specified, and an item construction algorithm, which manipulated complexity and redundancy, was implemented with a stochastic procedure to assign design elements. Images from this procedure were submitted to field testing to establish parameter values. Based on image model specifications presented above, a single image generator produced 96 templates, which was limited only by dimensional constraints of the physical cell structure. Figure 4 presents VDT construction specifications for item templates. Figure 5 presents sample isomorphs corresponding to templates produced by this procedure.

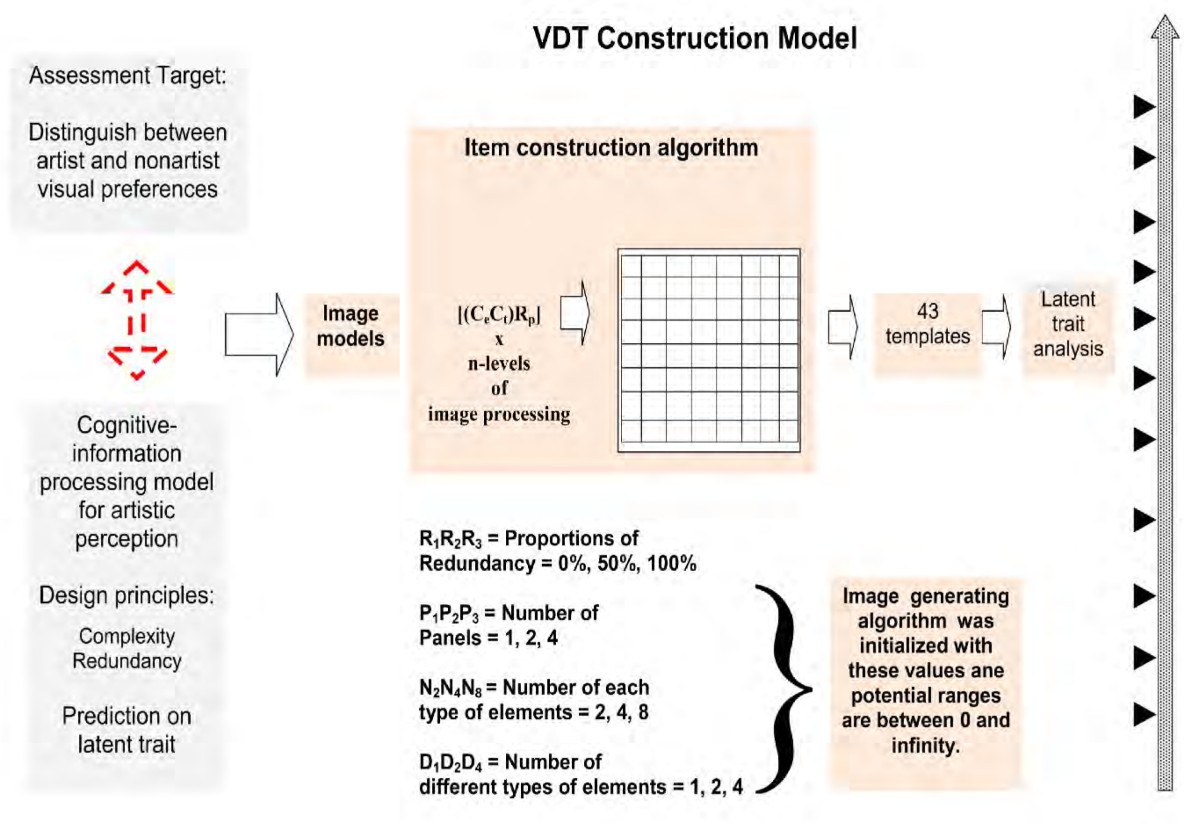


Figure 4. VDT rule-based image construction model

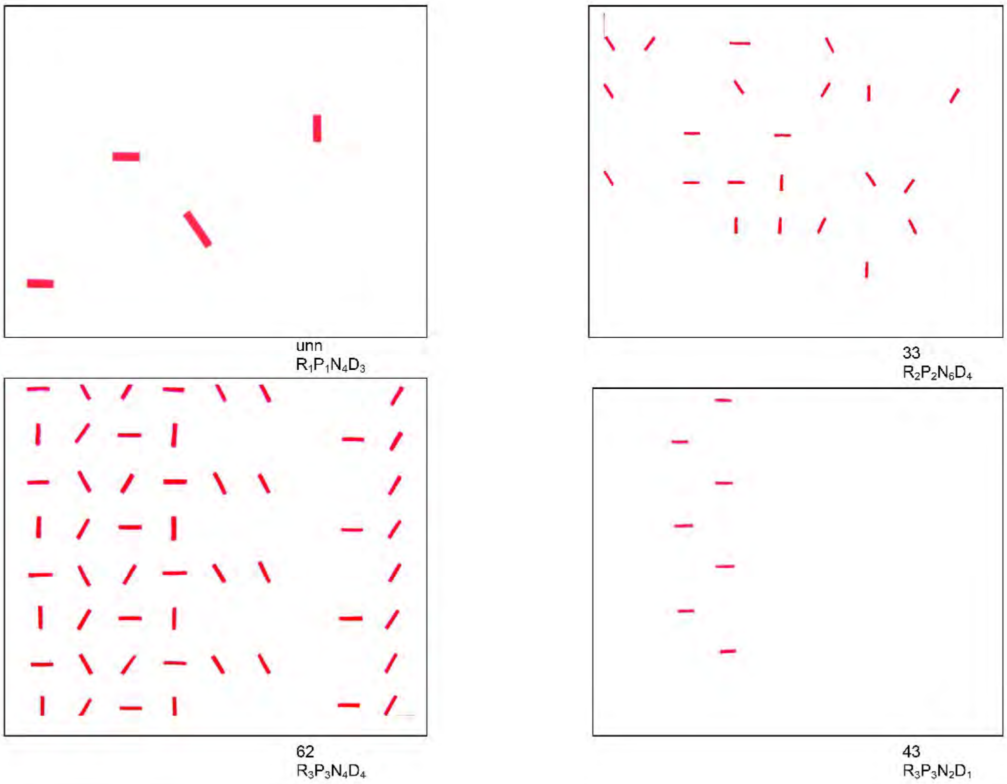


Figure 5. VDT sample isomorphs from a generative algorithm

A rule-based method was developed for objective image construction. Rule-based methods were originally developed for intelligence and achievement testing [31, 32]. This adaptation to AJ judgment aptitude integrates Eysenk's K factor with several ideas from experimental aesthetics and information theory. Together, they establish an image model, which operationally defines a visual preference construct with linear measurement properties. Subsequent studies would examine professional artist validation and aptitude status of this construct in developmental research [40].

A key innovation was a generative statistical algorithm that manipulated complexity and order (redundancy) separately in visual designs [33, 34, 35, and 36]. Based on Attneave's stochastic composition process (1957, 1959), this algorithm included a stochastic component that systematically manipulated only complexity and order (redundancy), and randomly assigned image elements to a design grid. This procedure reduces visual art to syntactic information expressed in stark abstract designs of black, white, and red. Using this algorithm and an incomplete factorial design in which 3 levels of 3 complexity factors were crossed with 3 levels of a redundancy factor [33], 84 pairs of images that contrasted higher and lower complexity levels were constructed. Visual preferences between image pairs were collected from several JOCRF examinee samples, and their responses were dichotomously scored to exploit Eysenck's research indicating artists prefer less-complex designs. Conventional psychometric analyses then identified two prominent factors that were called Simplicity and Uniformity [9, 25]. Original 84 items were reduced to 35 forced-choice items (Simplicity = 22 items and Uniformity = 13 items) and published as Visual Designs Test (VDT) [9].

6. Migration to figurative images

6.1 Background

Although VDT abstract consists of statistical images generated by an algorithm, they mimic minimalist images similar to contemporary neoplasticism, and professional artists in a validation study soundly endorsed their aesthetic value (*N*=66). Artist de-briefing interviews after the professional artist validation study revealed their interest in stochastic images, and artists from this sample frequently identified specific aspects of VDT abstract images that influenced their preference in presented image pairs.

In order to broaden validity foundations beyond minimal, nonrepresentational, abstract images, a study was conducted of examinee preference for more traditional, representational art. Of particular interest was comparability of visual preference for abstract images based on the VDT algorithm versus images that included semantic, expressive, and stylistic information. Are abstract and figurative images equally valid for evaluating AJ aptitude? In order to address this question, VDT generative algorithm was adapted for production of authentic figurative paintings.

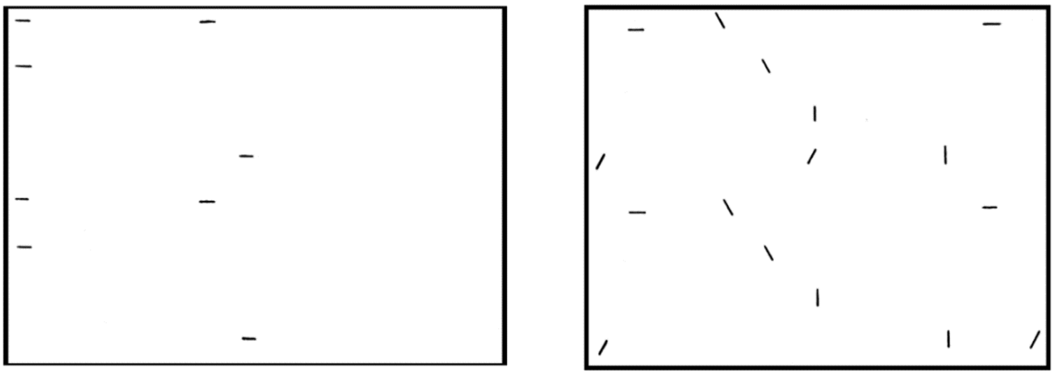
Not surprisingly, VDT generalization to figurative images raised enormous challenges. VDT abstract is a 1-layer image model, while figurative images in general consist of *n*-layers that are likely saturated with semantic, expressive, cultural, and syntactic information. Information density of figurative would obviously be much higher, and interactions would be expected across levels. This challenge is described below [37].

> The goal of the *n*-layer model is to generate items by manipulating a relatively large number of elements at two or more layers in a parent model. . . . unlike the 1-layer model where manipulations are constrained to a linear set of generative operations using a small number of elements [37].

Figure 6 presents both VDT abstract and figurative images, which contrasts syntactic structure between a single layer abstract image and a profoundly more complex figurative image. VDT abstract images are direct products of a generative algorithm, which systematically alters syntactic properties of complexity and redundancy. The challenge is to produce figurative images, which maintain comparable syntactic properties with VDT abstract images but also include levels of artistic information defined by content, style, expressiveness, and color.

Validity of any comparison between abstract and figurative images would depend on some convincing demonstration the cognitive-perceptual model that was supported during visual judgments of VDT abstract also applies to visual appraisal of figurative images. Consequently, figurative images were needed that would provide variation of syntactic properties within figurative images. In other words, several versions of figurative images would be needed which would present subtle complexity manipulations. In this manner, not only would comparability be established but validity of underlying perceptual mechanism could be evaluated to further extend the VDT cognitive model.

Abstract



Figurative

Figure 6. VDT migration to figurative images

Strategy to address this goal emphasized reproducing syntactic structure of specific VDT abstract images in figurative paintings during their production. Then producing iterations of the paintings with specific complexity manipulations.

Collaborating with a professional artist, figurative images were painted across five visual art styles (Fauvism, Post-Impressionist, Surrealism, Renaissance, and Baroque), which are presented in Figure 7. Three styles, Fauvism, Renaissance, and Baroque are representational, while Surrealism and Post-Impressionism paintings are nonrepresentational. Painted in oil or acrylic on canvas, they were especially created to reflect complexity and redundancy of several VDT abstract images. Each figurative image was painted four times to reflect complexity and redundancy levels of abstract images.

Figurative production of each style was staged in three separate sessions. During first painting session, the artist created five paintings independent of VDT abstract images, which established an artist baseline for each style. Then each painting was manipulated to represent proportional relations between complexity and redundancy in an abstract image. Artist then manipulated three separate complexity levels.

Fauvism

Renaissance

Baroque

Figurative images were painted in a variety of styles in order to examine preference by style interactions within context of complexity manipulations. Artist controlled complexity in each style by imposing a ratio of complexity to redundancy on each painting. This ratio was systematically manipulated across four paintings. During this procedure, artist maintained thematic coherence across entire set of complexity manipulations.

Post-Impressionism

Surrealism

Figure 7. Figurative styles were manipulated with a generative procedure.

Through this procedure, syntactic structure of VDT abstract images was systematically reproduced in figurative paintings.

Following steps summarize production of figurative paintings. First, the artist identified proportional relations between complexity and redundancy in five artist-preferred VDT abstract images. Professional artist preference for these images had been established in previous JOCRF field studies. Consequently, the artist established a formula -- one part complexity to one half redundancy, that is, 1:.5, then created paintings on canvases in five styles described above. This ratio, 1:.5, was reproduced in Post-Impressionist, Surrealism, Renaissance, and Baroque paintings. A fifth painting, Fauvist in style, presented complexity and redundancy in a 1 to 1 relation. These paintings established a syntactic baseline.

Figure 8 presents four VDT abstract images of differing complexity generated from an algorithm. Professional artist first reproduced proportional relations of complexity and redundancy in a Post-Impressionist figurative painting. Next, the artist

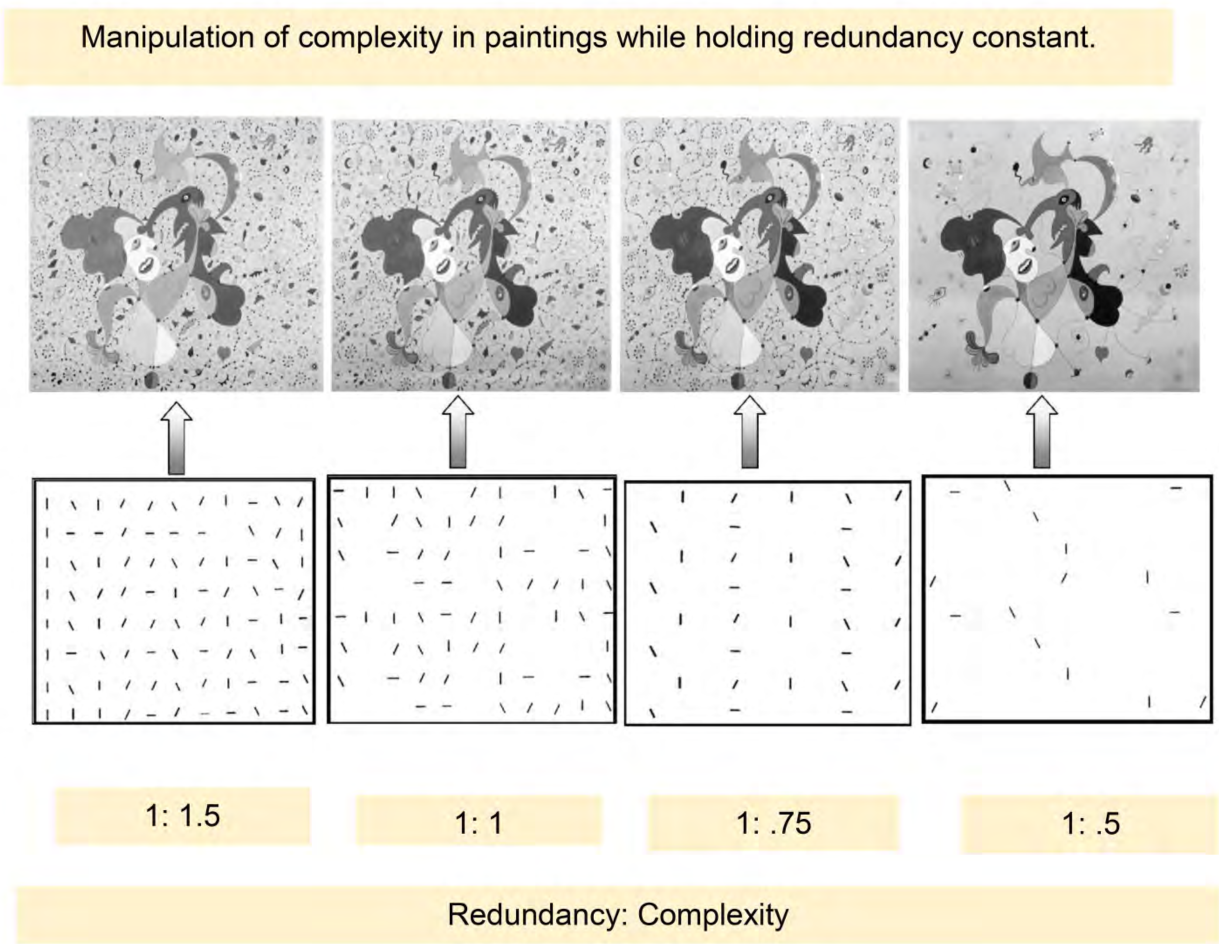


Figure 8. Manipulation of complexity in a Post-Impressionist painting was directly linked to generative algorithm for abstract images.

reproduced each painting three times but discretely increased complexity incrementally. Each reproduction was a step higher in complexity, while stylistic coherence was carefully maintained. Redundancy was not explicitly manipulated and remained fixed across paintings.

Following this procedure, an artist-preferred figurative image was paired with each complexity manipulation for each style. In other words, ffigurative images with syntactic properties highly preferred by professional artists were paired with a more complex painting. Finally, images were photographed, printed, and 20 image pairs bound into test booklets [38]). A complete set of paintings from this study are presented in an appendix. Then visual preferences were collected for both abstract and figurative images. A statistical comparison of these results is presented in sections below.

7. VDT Empirical Summary

7.1 Empirical calibration, measurement analysis

Early published reports describe VDT construct development with approximately 1,500 examinees from JOCRF testing offices [35]. Following expression presents the linear measurement model that was implemented to transform ordinal preferences scored for conformity with professional artist preference to a linear scale. Every response was coded either 0 or 1 depending on agreement with professional artists.

$$\Pi_{nix} = \frac{\exp \sum_{j=0}^{x} (\beta_n - \delta_{ij})}{\sum_{k=0}^{m_i} \exp \sum_{j=0}^{k} (\beta_n - \delta_{ij})]}$$

$x = 0, 1, \ldots m_i$

where $\delta_{i0} = 0$ so that $\exp \sum_{j=0}^{0} (\beta_n - \delta_{ij}) = 0$ and

$\exp \sum_{j=0}^{0} (\beta_n - \delta_{ij}) = 1$. X is count of completed steps.

Numerator contains only difficulties of completed steps, $\delta_{i1}, \delta_{i2}, \ldots \delta_{ix.}$ Denominator is sum of m_i + 1 possible numerators.

7.2 Item response (preference) analysis

Several empirical criteria are examined to establish psychometric quality of visual preference judgments. For example, consistency between image difficulty defined by agreement with professional artists and examinee preference propensity is needed to establish basic order between images and examinees. Some examinees showed a high propensity to agree with artist judgment, while others did not. Then statistical reproducibility of an image hierarchy that results from preference judgments needed verification, which established predictive foundations. Figure 9 presents response category parameters after VDT abstract images were presented to JOCRF examinees. Vertical axis presents probability of agreeing with professional artists, while horizontal axis is a linear scale that represents image difficulty. Probability of an examinee responding in a category (0=disagree with professional artist or 1=agree with professional artist) depends on difficulty of specific images and examinee preference propensity. For example, probability of an examinee with low preference propensity, approximately -1 logits, agreeing with an image of moderate difficulty, 0.0 logits is very unlikely, while probability of disagreeing is close to .8. These results show highly ordered relations between images and preferences.

```
+--------------------------------------------------------+
|CATEGORY   OBSERVED|OBSVD SAMPLE|INFIT OUTFIT| COHERENCE|
|LABEL SCORE COUNT %|AVRGE EXPECT|  MNSQ  MNSQ| M->C C->M|
|-------------------+------------+------------+----------|
|  0   0    2651  55|  -.70  -.70|   .99  1.03|  71%  76%| 0
|  1   1    2201  45|   .32   .32|   .99  1.02|  68%  62%| 1
+--------------------------------------------------------+
AVERAGE MEASURE is mean of measures in category.

        DICHOTOMOUS CURVES
P      ++--------------+--------------+--------------+--------------++
R  1.0 +                                                             +
O      |                                                             |
B      |0                                                           1|
A      | 000000                                               111111 |
B   .8 +       00000                                     11111       +
I      |            0000                             1111            |
L      |                0000                     1111                |
I      |                    000               111                    |
T   .6 +                       000         111                       +
Y      |                          000   111                          |
    .5 +                             ***                             +
O      |                          111   000                          |
F   .4 +                       111         000                       +
       |                    111               000                    |
R      |                1111                     0000                |
E      |            1111                             0000            |
S   .2 +       11111                                     00000       +
P      | 111111                                               000000 |
O      |1                                                           0|
N      |                                                             |
S   .0 +                                                             +
E      ++--------------+--------------+--------------+--------------++
       -2             -1              0              1              2
                       PERSON [MINUS] ITEM MEASURE
```

Figure 9. VDT response categories

7.3 Abstract items

In first of several studies, several hundred JOCRF nonartist examinees rated “attractiveness” of two sets of 45 VDT abstract images on a scale of 1 to 5. A Rasch model rating scale analysis found VDT images operationally to define a construct ranging from more-complex to less-complex. Figure 10 presents the image hierarchy. The higher rated, more-complex images are along the low end and lower rated, less-complex images are along upper portion. These preliminary results established coherence among ratings for images that only differed in complexity.

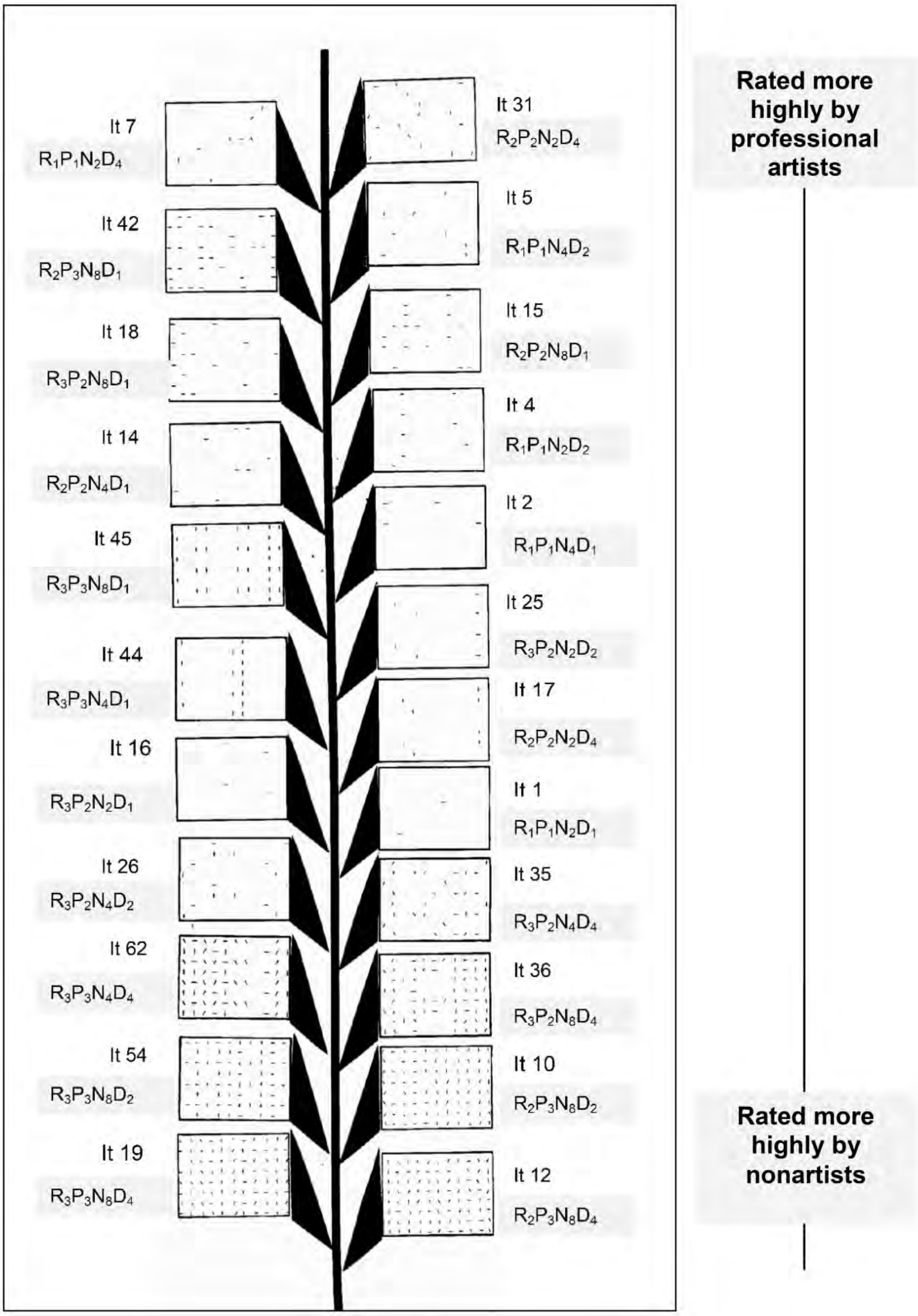


Figure 10. VDT abstract image hierarchy. Images lower on this higher hierarchy are rated higher by nonarts.

In a second study, images of contrasting complexity were paired and presented to examinees. Then principle components analysis was conducted of preferences, which identified to two prominent preference factors, Simplicity and Uniformity [9].

They were formulated into separate scales: Simplicity (22 items) and Uniformity scales (13 items), respectively. VDT Simplicity presents design pairs that differ in complexity defined by variety and frequency of elements. Uniformity pairs also differ in complexity but are defined by element dispersion and spatial orientation.

In general, image calibration with a Rasch model replicated a linear hierarchy presented in Figure 10. Fit, residual, and construct validity analyses are summarized in published reports [39]. Further studies collected visual preferences from professional artists for Simplicity and Uniformity scales and found their locations to differ significantly from nonartists. Nonartists fell significantly lower along the Simplicity construct than professional artists, while professional artists tended to cluster above a defined scale threshold [36, 41]. This image hierarchy, which consistently shows high psychometric reliability (>.90), and VDT abstract images has been in operational use in JOCRF testing offices for over 20 years.

7.4 Figurative items

After conclusion of VDT abstract validation, questions began to mount about comparability of AJ aptitude measurement based on VDT abstract versus figurative images. Consequently, a study was conducted to examine their similarities and clarify their differences.

Two sets of images were prepared for this study. First, thirty-four pairs of VDT abstract images organized on basis of results from professional artist validation were printed in booklets. Then VDT figurative images were similarly organized and printed in booklets. VDT figurative image pairs consist of 20 pairs of traditional paintings in five styles: Fauvism, Renaissance, Baroque, Surrealism, and Post-Impressionism that were specifically painted for this research according to a procedure described in preceding sections of this report.

Both abstract and figurative image pairs were presented to a JOCRF client sample with the question, "Which do you prefer?" Professional artist preference in each pair was keyed correct and responses were analysed with a probabilistic dichotomous Rasch model [42]. Figure 11 presents a calibrated hierarchy of figurative images based on this sample.

Vertical arrangement of paintings in Figure 11 indicates difficulty of agreeing with professional artist judgment. “Complexity level” indicates amount of complexity artist added to a painting. The “3rd“ level, for example, indicates highest complexity in each style. According to these results, four complexity levels of Post-Impressionist paintings were presented to examinees, and all were relatively easy for these examinees to agree with professional artists. In contrast, examinee preference was least similar to professional artists for Fauvist style paintings, which is located at top of hierarchy. Nonartist agreement with professional artists for Surrealism, Renaissance, and Baroque styles ranged between these extremes.

```
                                                           Painting          Complexity
                                                            style              level
-4    -3     -2     -1      0      1      2      3      4
|------+------+------+------+------+------+------+------| ---------------------------------
0                                  1                    1  Fauvism13                 1st
0                                  1                    1  Fauvism9                  3rd
|                                                       |
0                                 1                     1  Fauvism18                 2nd
|                                                       |
|                                                       |
0                               1                       1  Fauvism5                  ----
0                              1                        1  Renaissance6              ----
|                                                       |
|                                                       |
0                            1                          1  Surrealism2               1st
0                            1                          1  Baroque8                  ----
0                            1                          1  Renaissance16             1st
0                            1                          1  Baroque3                  3rd
0                           1                           1  Baroque20                 1st
0                           1                           1  Renaissance12             3rd
0                           1                           1  Surrealism7               2nd
0                           1                           1  Baroque15                 2nd
0                          1                            1  Renaissance1              2nd
0                          1                            1  Surrealism11              3rd
0                          1                            1  Surrealism17              ----
|                                                       |
|                                                       |
0                     1                                 1  Post-Impressionism4       1st
0                    1                                  1  Post-Impressionism10      3rd
0                    1                                  1  Post-Impressionism19      2nd
|                                                       |
|                                                       |
0                  1                                    1  Post-Impressionism14      ----
|------+------+------+------+------+------+------+------|
-4    -3     -2     -1      0      1      2      3      4

           1   1  2 2 24 4 45 33 22 1
2     9    4   7  4 5 9915 30180 75 715  6  1     2     1   Person
            T      S      M      S      T                   Measure
                                                            Distribution
```

Note. N = 462 examinees.

Figure 11. VDT figurative image hierarchy. Within a style, each painting is identical except for a complexity manipulation. Higher complexity level indicates incrementally higher complexity level.

Another pattern appears within this distribution of agreement with professional artists. Within Post-Impressionism, Surrealism, and Fauvism, the image with least complexity, surprisingly, was most consistent with professional artist preferences. In other words, when lowest complexity level paintings, which are indicated by "----" in Figure 11, were presented in pairs, nonartists tended to agree with professional artists more than when alternative pairs were presented. In contrast, lowest complexity level paintings in Baroque and Renaissance show least agreement between nonartists and professional artists. Preference for figurative images in mid-range are close to chance, which suggests that both Post-Impressionist and Fauvist styles could be highly effective in an AJ scale of figurative images. In general, these results, as expected, show complex interactions among style, content, and syntax.

7.5 Construct validity studies

Construct validity of the hierarchy was consistent with theoretical expectations, that is, visual preference higher on the construct map is systematically linked to shifting syntactic structure of complexity and redundancy objectively manipulated during template production. VDT reliabilities are typically high (>.90). Construct validity has been statistically examined by regressing item difficulties on design components (C_1, C_2, R_1, C_2XR_1), which found R^2 = .79 corrected for attenuation.

Conventional psychometric studies have consistently shown VDT internal structure and reliability to be high (> .90), and empirical studies support convergent, divergent, and professional artist validity [9, 35, 36, 41]. Developmental implications of Simplicity and Uniformity were also investigated by JOCRF and Chicago Public Schools with school children [32]. Cross-cultural robustness of Simplicity and Uniformity was supported by studies with inner-city Chicago and Portuguese school children [26]. These results are interesting as cross cultural comparisons found virtually identical scores.

In addition to studies described above, theoretical validity was investigated of the hierarchal image structure that was obtained after raw scores were transformed to linear measures. In this statistical procedure, VDT abstract calibrations were regressed on orthogonally coded item components of complexity and redundancy (number of panels, number of total elements in panel, number of element types in panel, and interaction of element types and redundancy). Results showed systematic relations between item components and logits difficulties to account for almost 80 percent of preference variance (R^2 = .79; F = 56.59, P < .001). These results support hypothesized relation between visual preference and complexity.

More recent studies have examined convergence of high scores on career selection. This research examined relations between VDT abstract scores and arts-related career choices in a data base of over 10,000 JOCRF examines. These results found significant positive correlations between VDT abstract and career choices. Examinees with arts-related occupational backgrounds expressed preferences for VDT abstract images that were significantly correlated with professional artists.

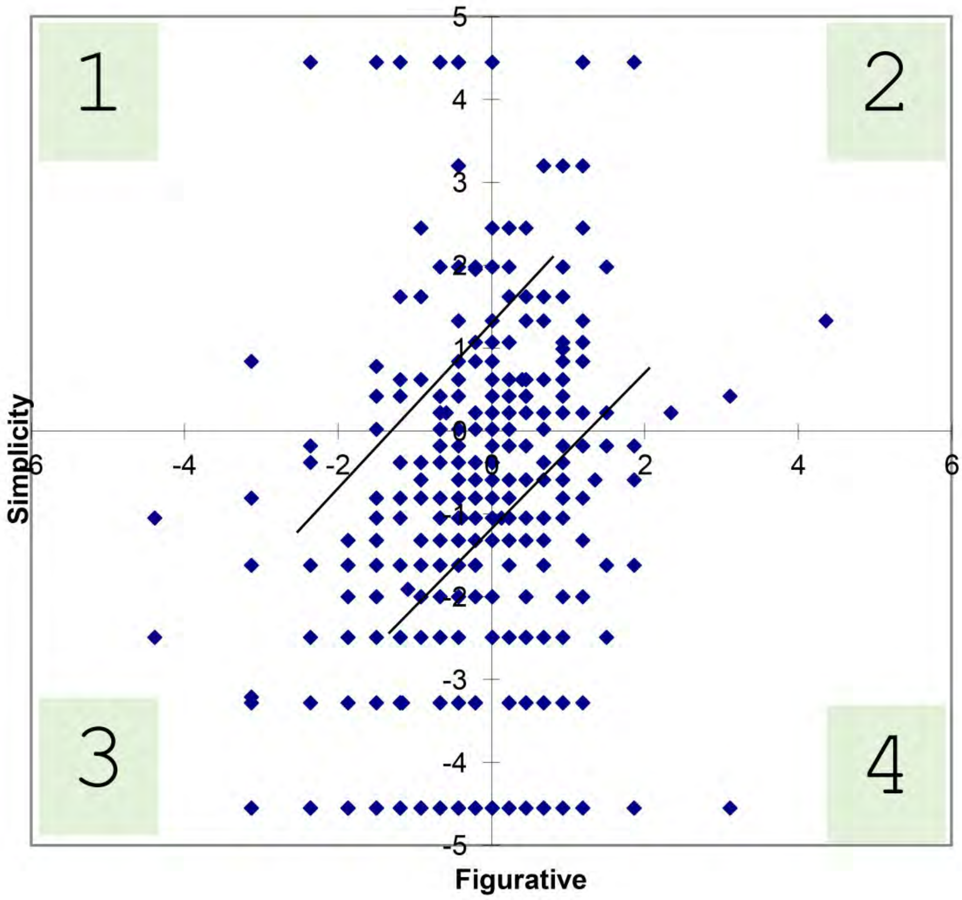
7.6 Professional artist validation

VDT artist validation was conducted with a sample of professional artists from across a range of artistic media in three metropolitan areas: New York City (4), New Orleans (17), and Chicago (41). Their ages ranged from 19 to 75 years (Mn = 40.9, SD = 13.1) with a median of 39 years. About 60 percent were females. All artists were actively engaged in design and production of visual artworks (*N*=66). Simplicity and Uniformity items were administered to both groups. Difference between nonartists and professional artists was statistically significant, and sstandardized difference was .44 SD units. Details of that study were published [36]. A separate follow-up validation study was conducted with VDT figurative images using abstract image calibrations obtained from professional artists in VDT abstract validation.

7.7 Comparability of Abstract and Figurative constructs

Construction of a figurative scale with syntactic properties derived directly from abstract images generated from a rule based algorithm raises questions about comparability of preference judgments. Do examines with high AJ aptitude measures based on abstract preference judgments also receive high measures on a figurative construct? Likewise, are AJ aptitude measures interchangeable between abstract and figurative scales? In order to address these questions and others, abstract and figurative examinee measures were statistically correlated and those results appear in Figure 12. Raw scores in this plot have been transformed to linear person measures (logits) for VDT abstract and figurative scales, respectively.

As expected, figurative images full of semantic content, stylistic variation, and complex expressiveness introduced considerable unexpected variability into the VDT preference model. These results suggest the simple VDT complexity model is less effective when images are not random patterns. Meaningfulness and content become prominent in figurative images, and coherence and style influence visual preference. Yet, despite these complications, significant positive correlation was obtained between abstract and figurative examinee measures. Corrected for attenuation, this correlation was over .40, which establishes empirical foundations for generalizing the VDT abstract algorithm to synthetic production of rule-based figurative images. This correlation would be expected to be even higher if professional artists had been included in this sample.



N = 435 nonartist adult examinees.

Figure 12. Correlation of examinee linear measures on both abstract and figurative constructs. Examinees in quadrant 4 showed much higher agreement with professional artists when images were figurative. Examinees in quadrant 1 agreed more with professional artists when images were abstract.

Three results presented by this plot based on nonartists are especially important. First, most examinees who were in middle of abstract aptitude distribution are also in middle of figurative distribution. Their AJ sensitivity does not appear to interact with image content, that is, abstract versus representational content. However, these results show two subsets of examinees that substantially distort relations between abstract and figurative measures. First, a group of examines with very low Simplicity measures, showed much higher agreement with professional artists when presented figurative images, which is very surprising. Second, another examinee group showed very high Simplicity measures, yet they showed very low agreement with professional artists when presented figurative images. In general, VDT figurative results show strengths and weaknesses of the AJ aptitude processing model.

8. Discussion

8.1 Complexity

Despite over 125 years of empirical research, confusion about complexity, visual preference, and visual arts continues to muddle AJ discussions. In this research, complexity was defined by a simple criterion of frequency. Number of elements, types of elements, and their frequency contributed to higher complexity. Redundancy was controlled by constraints on the stochastic generator. More importantly, this simple model for manipulating complexity was supported by relations with professional artist preference. Image variation based on this definition of complexity led to significant differences between professional artists and nonartists. Much confusion in contemporary literature about complexity and redundancy is related to empirical and philosophical studies that neglect to consider differences between professional artists and nonartists.

8.2 Generative art and psychometric image models

An issue of contemporary importance concerns role of generative art in cognitive processing models, which was central to this research. Generative art was instrumental to establishing a cognitive-perceptual image model that was successfully validated by professional artists. Consequently, precise contribution of generative art to this advance is a question of some interest.

A cognitive item model usually requires several preparatory steps before producing items for a test design. VDT and its implementation of generative art required following steps:

1. *Assessment target.* Declare an explicit assessment target, which in this research was AJ aptitude.
2. *Review literature.* Identify empirical and philosophical literature related to assessment target. For example social research is replete with studies that examine influences on AJ – criteria that influence AJ. While complexity and redundancy were selected for this research, alternatives such as expressiveness and coherence could easily have been just as effective.
3. *Establish empirical relations*. Relations between empirical criteria and assessment target establishes an “idea”, which acquires dynamic function. In other words, idea of criteria and target must establish functional interdependence.

4. *Empirical verification.* Design an experiment that demonstrates your idea (criteria and target) is empirically related to test performance. For example, demonstrate variation of image complexity or some other criterion such as expressiveness, or coherence is empirically related to AJ.
5. *Formalize images*. Develop separate images that demonstrate inter-relations of criteria and target.
6. *Construct development.* Identify thresholds that indicate qualitative contours and transitions across purported linear construct.
7. *Parameterization*. Collect field data to identify parameter values. Rasch measurement model was applied for this purpose in this research.

These steps complete a process of conceptualization, construct formulation, and measurement parameterization, which occurs during psychometric construction of any idea. Present research differs because a generative mechanism was added to the process, which increased consistency of preference responses and increased clarity of validation. By linking image construction, which is defined by explicit criteria of complexity and redundancy to a generative stochastic algorithm, a background field was created in images that was irrelevant to the dynamic function presented in the cognitive-preference model. Implementing the generative stochastic algorithm effectively eliminated visual background from interfering with targeted preference.

References

[1] Eysenck, H. J. (1941). Type factors in aesthetic judgments. *British Journal of Psychology, 31,* 262-270.
[2] Chatterjee, A. (2011). Neuroaesthetics: A coming of age story. *Journal of Cognitive Neuroscience*, *23*, 53-62.
[3] Fechner, G. T. (1865). Weber die Fragen des Golden Schnitts. *Archiv. f. d. Zeichenenden Kuenste* (Nauman-Weigel), *11*, 100-112.
[4] Fechner, G. T. (1876). *Vorschule der aesthetik.* Leipzig: Breitkopf and Hartel.
[5] Birkhoff, G. D. (1933). *Aesthetic measure*. Cambridge, MA: Harvard University Press.
[6] Eysenck, H. J. (1940). The general factor in aesthetic judgments. *British Journal of Psychology, 3,* 94-102.
[7] Eysenck, H. J. (1968). An experimental study of aesthetic preference for polygonal figures. *Journal of General Psychology, 79*, 3-17.
[8] Eysenck, H. J., and Castle, M. (1970). Training in art as a factor in the determination of preference judgements for polygons. *British Journal of Psychology, 61*, 65-81.
[9] Bezruczko, N., and Schroeder, D. H. (1989). *Technical Report 1989-2. Artistic Judgment Project I: Internal-structure analyses.* Chicago: Johnson O'Connor Research Foundation, Inc.
[10] Bezruczko, N., and Schroeder, D. H. (2002) *Statistical Bulletin: Artistic Judgment: Figurative Pilot.* Chicago: Johnson O'Connor Research Foundation, Inc.
[11] Berlyne, D. E. (1971). *Aesthetics and psychobiology.* New York: Appleton-Century-Crofts.
[12] Berlyne, D. E. (1974*). Studies in the new experimental aesthetics: Steps toward an objective psychology of aesthetic appreciation*. Washington, DC: Hemisphere.
[13] Martindale, C., Moore, K., and Borkum, J. (1990). Aesthetic preference: Anomalous findings for Berlyne's psychobiological theory. *American Journal of Psychology, 103*, 53-80.
[14] Attneave, F. (1954). Some informational aspects of visual perception. *Psychological review, 61*, 183–193.
[15] Attneave, F. (1957). Physical determinants of the judged complexity of shapes. *Journal of Experimental Psychology, 53,* 221-226.
[16] Attneave, F. (1959). Stochastic composition processes. *Journal of Aesthetics and art Criticism, 17*, 503-510.
[17] Noll, A. M. (1966). Human or machine: A subjective comparison of Piet Mondrian's "Composition with Lines" (1917) and a computer-generated picture. *The Psychological Record, 16*, 1-10.
[18] Noll, A. M. (1972). Effects of artistic training on aesthetic preferences for pseudo-random computer-generated patterns. *The Psychological Record, 22*, 449-462.
[19] Platt, J. R. (1961). Beauty: Pattern and change. In D. W. Fiske and S. Maddi, (Eds.), *Functions of varied experience.* Homewood, Illinois: The Dorsey Press.
[20] Moles, A. (1958). *Information theory and esthetic perception*. Urbana, IL: University of Illinois Press. Originally published as *Theorie de l'information et perception esthetique* by Flammarian and Cie.
[21] Leder, H., Belke, B., Oeberst, A., and Augustin, D. (2004). A model of aesthetic appreciation and aesthetic judgments. *British Journal of Psychology, 95*, 489–508.
[22] Leder, H. (2013). Next Steps in Neuroaesthetics: Which processes and processing stages to study? *Psychology of Aesthetics, Creativity, and the Arts , 7,*

27–37.
[23] Schmidhuber, J. (1997). Low-complexity art. *Leonardo, 30*, 97-103.
[24] Ichijo, A., Hayami, Y., Takyo, S., and Niimi, T. S. R. (1998). *De Stijl 1917-1932: Art and Environment of Neoplasticism*. Toyko: Kawade Shobo Shinsha.
[25] Bezruczko, N., and Schroeder, D. H. (1987). *Visual Designs Test: Abstract.* Chicago: Johnson O'Connor Research Foundation, Inc.
[26] Bezruczko, N., and Fróis, J. P. (2011). Comparison of several artistic judgment aptitude dimensions between children in Chicago and Lisbon. *Visual Arts Research*, *37*, 1-15.
[27] Lindgaard, G., Fernandes, G., Dudek, C., and Brown, J. (2006). Attention web designers: You have 50 milliseconds to make a good first impression! *Behaviour & information technology*, *25*, 115-126.
[28] Tuch, A. N., Presslaber, E. E., Stöcklin, M., Opwis, K., and Bargas-Avila, J. A. (2012). The role of visual complexity and prototypicality regarding first impression of websites: Working towards understanding aesthetic judgments. *International Journal of Human-Computer Studies, 70,* 794–811.
[29] Dickie, G. (1962). Is psychology relevant to aesthetics? *Philosophical Review, 71*, 285-302.
[30] Reber, R. (2008). Art and its experience: Can empirical psychology help assess artistic value? *Leonardo, 41*, 367-372.
[31] Embretson, S., and Gorin, J. (2001). Improving construct validity with cognitive psychology principles. *Journal of Educational Measurement*, *38*, 343-368.
[32] Hornke, L. F., and Habon, M. W. (1986). Rule-based item bank construction and evaluation within the linear logistic framework. *Applied Psychological Measurement, 10*, 369-380.
[33] Bezruczko, N. (1989). *Research Memorandum 1989-3. Item specifications for 84 forced-choice VDT items.* Chicago: Johnson O'Connor Research Foundation, Inc.
[34] Bezruczko, N. (1990). *Construction and validation of a scale for Eysenck's K factor.* Presented at Eleventh International Colloquium on Empirical Aesthetics, Budapest, Hungary.
[35] Bezruczko, N., and Schroeder, D. H. (1990). *Artistic Judgment Project II: Construct validation* (Technical Report 1990-1). Chicago: Johnson O'Connor Research Foundation. (ERIC No. 017 064)
[36] Bezruczko, N., and Schroeder, D. H. (1991). *Artistic Judgment Project III: Artist validation* (Technical Report 1991-1). Chicago: Johnson O'Connor Research Foundation.
[37] Gierl, M. J., Lai, H., and Breithaupt, K. (2012, April). Methods for creating and evaluating the item model structure used in automatic item generation. Paper presented at the Annual Meeting of the National Council on Measurement in Education, Vancouver, BC, Canada.
[38] Bezruczko, N., Borgognoni Vimercati, A., and Callipari, P. (2000). Visual *Designs Test: Figurative Pilot Edition.* Rome, Italy: Courage Press.
[39] Bezruczko, N. (2002). A multi-factor Rasch scale for artistic judgment. *Journal of Applied Measurement, 4,* 360-399.
[40] Bezruczko, N., and Schroeder, D. H. (1995). Development of visual preferences in art-trained and non-art-trained schoolchildren*. Genetic, Social, and General Psychology Monographs, 122*, 179-196.
[41] Bezruczko, N., and Schroeder, D. H. (1994). Differences in visual preferences and cognitive aptitudes of professional artists and nonartists. *Empirical Studies of*

the Arts, 12, 19-39.
[42] Wright, B. D., and Stone, M. H. (1979). *Best Test Design.* Chicago: MESA Press.
[43] Bezruczko, N. (2014). Automatic Item Generation Implemented for Measuring Artistic Judgment Aptitude. *Journal of Applied Measurement,* (in press).
{44} Eysenck, H. J. (1972). Personal preferences, aesthetic sensitivity and personality in trained and untrained subjects. *Journal of Psychology, 40*, 544-557.
[45] Galanter, P. (2003). What is Generative Art? Complexity theory as a context for art theory. In GA2003–6th Generative Art Conference, Milan.
[46] den Heijer, E., and Eiben, A. E. (2010, July). Using aesthetic measures to evolve art (pp. 1-8). In *Evolutionary Computation (CEC),* 2010 IEEE Congress.

Appendix

VDT

Figurative Images

(Figurative syntax assigned by generative algorithm)


1-A


1-B


2-A


2-B


3-A


3-B


4-A


4-B


5-A


5-B


6-A


6-B


7-A


7-B


8-A


8-B

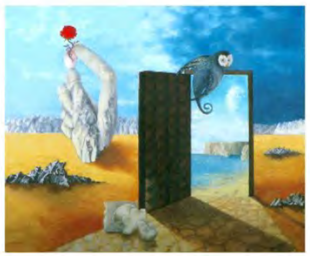

9-A


9-B


10-A


10-B


11-A


11-B


12-A


12-B


13-A


13-B


14-A

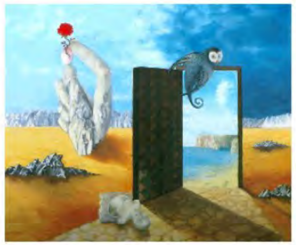

14-B


15-A


15-B


16-A


16-B


17-A


17-B


18-A


18-B

19-A

19-B

20-A

20-B