What have Fractals got to do with it?
Individual Differences in Aesthetic Responses

Thesis submitted in accordance with the requirements of the University of Liverpool for the degree of Doctor in Philosophy by

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Preface

"The wildness pleases. We seem to live alone with Nature. We view her in her inmost recesses, and contemplate her with more delight in these original wilds than in the artificial labyrinths and feigned wildernesses of the palace" (A.A. Cooper, third Earl of Shaftesbury, The Moralists, 1709/1999)

The impact that aesthetics have on our daily experiences is often underestimated and considered a qualities of the arts, however the subsequent behavioural impact means that our daily visual environments are important to understand aesthetically. Aesthetic judgments are made daily, without conscious awareness however, from a scientific point of view, encapsulating what contributes to a positive or negative aesthetic experience has been problematic. The field has suffered from a lack of coordinated cross-disciplinary effort, with many areas such as cross-cultural universals and individual differences remaining under-researched.

Given the long history of segregation between the various field studying aesthetic responses to art, nature and landscapes, this thesis will explore the highly variable findings regarding individual differences within the field. It achieves this through a multidisciplinary approach bringing together knowledge from the fields of psychology, computer science, physics as well as landscape planning and design research.

Environmental scenes contain both Euclidean and natural (Fractal) geometry, and whilst to date a wide-range of studies have explored aesthetic responses to simple Euclidean geometric shapes, there is limited evidence exploring aesthetic responses to fractal geometry as an individual construct.

The stimuli of choice for this project are computer generated mathematical fractal patterns. Mathematical fractal patterns have an advantage over natural fractals as they contain only fractal content. Whereas naturally occurring fractals will also contain information such as colour, which can result in response bias. A shortcoming of course, is that the computer-generated shapes that have limited ecological validity and results are only tentatively extrapolated to responses to the fractal patterns in the real word.

Sample sizes used in this thesis are large and taken from a cross and subcultural background, in some cases over 400 participants took part in individual studies from over 30 countries. These large samples permitted detailed analysis of the strength of the mid-range hypothesis and complexity hypothesis in predicting preference based on a number of individual factors including country, continent, environment, age and gender. The findings demonstrate that aesthetic responses to fractal patterns can be predicted by continent, environmental classification, age and gender.

Acknowledgements:

I have always, since childhood, had an interest in visual art and the beauty in nature. Fractal geometry is a fascinating subject to me and I am happy to have had the opportunity to spend time getting to know the subject of fractal aesthetics inside and out. To have the chance to contribute new knowledge to the field is a privilege. Conducting my thesis has truly changed the way I see the world. I see and appreciate natural patterns, which after extensive research, only enhanced the beauty in my world and I am very grateful for this.

These four years have been a challenging trip, with both ups and downs. I have many people to thank along my journey. First and foremost is Dr Alex Forsythe whose supervision, knowledge, friendship and endless encouragement have helped me grow as an academic and a person. You have been an inspiration along the journey and I will be forever grateful. My other colleagues for helping me progress through my PhD, in particular Prof Ronan Reilly for his seemingly endless hours of patience and assistance, which he so graciously offered. Prof Richard Taylor for generating the images and providing the inspiration and the majority of the previous research in the field of fractal aesthetics and all other colleagues and office buddies I have had the pleasure of meeting over these 4 years. Thank you to all my family and friends, particularly my parents whose unwavering confidence, belief and love have helped me in everything I do, and last but certainly not least my eternal gratitude and thanks to my new husband Tom- you have been my shoulder to cry on in the difficult times and my partner in celebrating the good times- now onto the next steps together.

"The voice of nature loudly cries,
And many a message from the skies,
That something in us never dies."
Burns, (1790)

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1.0 The Foundations of Aesthetic Preference; Philosophy and Early Experimental Aesthetics.

This first chapter explores the historical foundations and philosophical roots of the study of aesthetics to ground the thesis firmly within its roots. It explores the initial philosophical questioning by the Ancient Greeks, Plato and Aristotle, who attributed beauty to a function of the object and a pale imitation of the world of Gods. Others continued this exploration in philosophy including Baumgarten who coined the term 'aesthetics' and Kant whose musings broke the experience of beauty into different experiences depending on the emotional responses for different stimulus (i.e. Art, everyday and Natural scenes). The section will then briefly present the findings from early empirical investigations into aesthetics by Gustav Fechner who is often considered the father in the field of empirical aesthetics. Finally the chapter will touch on the early quest to understand and predict general aesthetic perceptions conducted by Berlyne, Birkhoff and Eysenck and frame the current trends in the academic study of aesthetics discussed in subsequent sections.

1.1 Historical and Philosophical foundation of Aesthetics

Contemplation of aesthetic experience can be traced back as early as the Ancient Greeks. These philosophical musing, focusing on sensation and perception, were the first in a long history of what is now considered the science of aesthetics.

Plato (428BC-348BC) didn't much like the arts. He disapproved of the power that art and poetry had to seduce people, “banning” Artists from is ‘ideal state’ in ‘The Republic’ (c375BC), his Socratic dialogue outlining justice, order and character of the city state and the man. Plato valued the metaphysical belief, that the world we experience is a pale imitation of that which is experienced by the Gods. The Gods world was the true world, a world that we cannot perceive. Our world is an imitation of the ‘true’ world. Art was twice removed from the trust, as it did not even demonstrate skill in our imitation world.

Agreeing with Plato’s metaphysical ideas (but not his extreme views), **Aristotle (384BC-322BC)** offered a more in depth account of Art in Poetics (c. 335bc). Aristotle’s work laid the foundation for modern philosophical approaches to aesthetics. His writings focused on the experiences of emotions. Exploring the power of Artistic stimulus, Aristotle focused on the experiences of emotions and how they could provoke pain and pleasure. The viewer played a key role because personal experiences in life meant that we experienced individual emotions in different ways. The idea of exploring how our experiences shape our reactions to art and beauty is still very much the focus of modern day scientific aesthetics research, and is of high importance within this thesis. Aristotle separated our experience of art as being somehow different to reality, but noted that the affective response felt when viewing art is dependent on our relationship in reality.

The metaphysical view was adopted and explored further by the religious scholars **St Augustine (354 AD- 430 AD) and St Thomas Aquinas (1225-1274**). St Augustine asserted that anything possessing a sense of order, unity and proportion is perceived as beautiful, because it reflects a higher order of the true world of the Gods. St Thomas Aquinas built on these ideas arguing that beauty evokes a restful and harmonious state, which is not down to any visual experience per se, but down to our faculty of knowing, or our cognitions involved in the perceptual experience. Both of these ideas have been supported through modern scientific explorations. Order and unity do indeed play a major role in our aesthetic perceptions, as does or personal experience. Cognition is the function by which our judgments of beauty are made alongside the related processes of memory and emotion. Many new psychological theories of aesthetics attempt to explore the areas of the brain involved in our experiences of beauty.

Alexander Baumgarten is widely attributed to giving the field its modern name in 1735 when he established aesthetics as a distinctive branch of philosophy. Aesthetics, by his definition, became the concept of beauty gathered through the senses. Baumgarten took the field beyond the study of art and defined aesthetics as the ‘science of sensible knowledge’ opening the area to all of our aesthetic experiences whether they are in art, nature or daily life. However, perhaps the most recognised and commonly cited philosopher in the field, **Immanuel Kant** who began his exploration of aesthetics in his work Critique of Judgment (1790) felt differently. Kant was the first to exclusively write about this concept of aesthetics as a sensory and perceptual experience and believed beauty was an entirely subjective experience because preferences differ from person to person. He did however state that there was a universal dimension to beauty; Universals which could be collectively experienced when engaging with a piece of art or beautiful stimulus.

Kant was among the earliest philosophers to discuss aesthetics in relation to nature. Defining our aesthetic responses to nature as the sublime. Kant argued that the sense of awe and wonder experienced towards nature could be related directly to matters of survival. For example positive (safety and beauty), or negative (power or danger) sublime experiences, such as a storm or rocky sea, generates unexpected feelings of delight and our engagement with reality is altered, time and space become enlarged and awe inspiring.

Kant talked of aesthetic experiences as being ‘disinterested’. By this he means we are not actively seeking aesthetic stimulus in our everyday navigation of the world. Our experiences of beauty arrive suddenly with novel or interesting stimulus, at which point the cognition involved in aesthetic perception is kick started. Our experiences and existing cognitive schemas (the ideas and expectations involved in a particular situation) are essential when classifying beautiful or appealing objects. Kant's ideas had, and continue to have a profound affect on the modern day research into aesthetics both in philosophical, psychological and artistic disciplines. His work preceded many of the later empirical investigations, and his thinking has inspired a continued push to understand this complex concept that is aesthetics.

The area of aesthetics in philosophy has a long and rich past, and the above summary has provided just a brief insight into its history. Whilst this area is still under exploration in modern philosophy, many of the ideas introduced by philosophers have inspired the exploration of aesthetics from a psychological point of view. Many of the modern theories are supported by philosophical ideas, such as the properties of the stimulus and their effects of aesthetic responses and well as the impact of personal experience and cognition on our reactions to art and other aesthetics scenes and objects.

It is important to recognise the philosophical foundations. Modern research has not generated such ideas from non-existence, but with modern research methods we are able to unpick the philosophical ideas and make confident practical and theoretical assertions about our responses to aesthetic stimulus.

1.2 Foundations of Experimental Aesthetics

Gustav Fechner (1801-1887) opened arguably the first experimental psychological laboratory in the world, which to many signifies the start of modern Experimental Psychology as a whole. Fechner had an interest in studying all aspects of the senses. He made this clear when outlining the research aims for his lab with the study of aesthetic responses immediately following psychophysics thus establishing aesthetics as the second oldest filed in modern experimental psychology.

The first empirical investigations took place in 1871 at Dresden Museum. The study involved 2 versions of Holbein's *Madonna with Burgomaster Meyer (Fig 1.1)*

Figure 1.1: Holbein's Madonna with Burgomaster Myer (1528)

Spectators were asked to write down their impressions of each painting- including their aesthetic reactions. Unfortunately this study was ultimately unsuccessful. Spectators were unclear of what they were required to do and Fechner received few usable replies, however it marked a movement from the philosophical investigation of authors personal experiences and moved aesthetics into the experimental domain in which responses where averaged in an attempt to predict a general universal aesthetic response to stimulus.

Fechner's *Elements of Aesthetics* (1876) outlines his area of study in detail, it focused on bottom-up approached to aesthetics and as such looked at structures, shapes and colours from which aesthetic responses were, he believed, constructed. Fechner recognised the challenges of deconstructing art from a quantifiable whole for scientific study so his work looked mainly at aesthetic responses to shapes, in particular the Golden Section (or Golden Ratio); two quantities are in the golden ratio if their ratio is the same as the ratio of their sum to the larger of the two quantities. This ratio has a long history in science and art. It was discussed in the time of the Ancient Greeks in relation to experiences of aesthetic pleasure and it can be found in many works of art, such as Leonardo Di Vinci, and Salvador Dali as well as being found in appealing facial structure and nature. The face of the *Mona Lisa* (Figure 1.2) fits perfectly into a golden rectangle, although it is a matter of debate if Di Vinci purposefully integrated a golden ratio in his artworks.

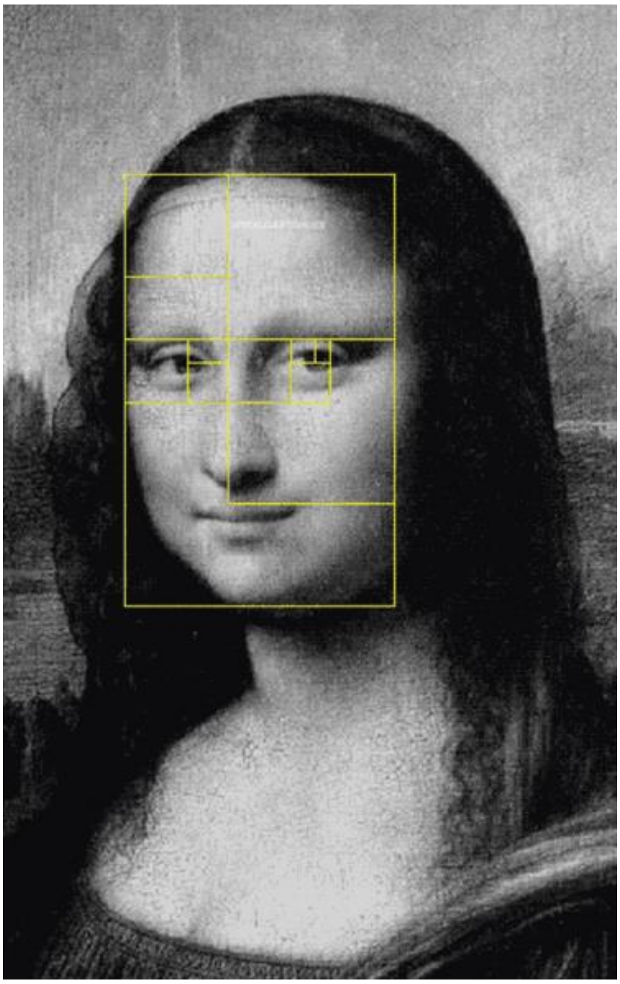

*Figure 1.2: Di Vinci's Mona Lisa, illustrating golden ratio**

* Golden Ratio: divide a line into two, and the longer part divided by the smaller part is equal to the whole length divided by the longer part.

Perhaps the largest impact Gustav Fechner had on Experimental Aesthetics today is the detailed explanations of methodology to test aesthetic responses. He outlined several methods:

- *The Choice Method*: Participants are asked to choose a stimulus image based on aesthetic judgments.
- *Method of Use*: Participants assess objects by their purpose and how this impacts aesthetic appeal.
- The *Method of Production:* Participants were asked to draw their ideal shape, or frame a composition based on aesthetic judgments.
- *Ordering technique:* Stimuli are presented to the participants to be ordered from highest to lowest preference. It can be used with any number of stimuli.

- *Paired comparisons:* Participants are presented with 2 stimuli and asked to select the one they find most appealing, beautiful, interesting etc. from the pair.
- *Rating Scale method:* Participants are asked to rate stimulus on a scale, either discrete (such as a likert scale) or continuous (any number from within a defined range) variables.

The method of production received little attention in the field until recent research adopted the method using computational advances of composition and framing. The work of McManus (2011) demonstrated how different types of stimulus could be tested for aesthetic value. Whilst the method has been applied to art, music and everyday objects, it is still the case that the most common stimuli used in experimentation are geometric shapes, isolated colours and tones. Other methodological techniques derived from Fechner including the Ordering technique, the Paired Comparisons, and the Rating Scale method, which will all be discussed in detail in later sections (Chapter 6).

Fechner laid the foundations for current trends of empirical aesthetics; he moved the field from a largely philosophical subject, to an area subject to stringent scientific measurement. He touched on many key areas that were later explored in detail in the field, including mental processes associated with aesthetic responses, bottom-up variables such as similarity, content, sequence, complexity, novelty and interest and their impact of aesthetic response. Of particular relevance to this thesis is the principle that suggests pleasant stimuli must provide a balance between order and complexity.

George Birkhoff (1884-1944) was an eminent American mathematician. Towards the end of his career, as it the common trend in empirical aesthetics, his thinking became focused on aesthetics responses to art, music and poetry. His book Aesthetic Measure (1933) proposed a mathematical theory of aesthetics and attempted to classify a formula that could represent our aesthetic responses to certain stimuli within a group.

$$M=O/C$$

Birkhoff's (1933) formula, expressed above, explained aesthetic measure (M) within a set of stimulus, as a function of order (O) and complexity (C). He was the first to reduce aesthetic response to a simple formula, however this is linked to many previous theories of philosophy in which unity, harmony and order where contrasted against diversity, multiplicity and complexity.

He believed Order (O) was a positive contributor to Aesthetic Measure (M) and Complexity (C) contributed negatively. Whilst this is still an area of debate (Forsythe et al; 2008), his acknowledgement that preferences are driven by the relationship between these 2 variables is still widely considered valid today. Complexity (C) is a factor that drives attentional effort and this effort needs to be compensated by the reward of unity or order (O) to create a positive aesthetic response.

Birkhoff's (1933) *Aesthetic Measure* covered a wide range of stimulus and discussed the method of measurement and classification. Music, Art and Poetry were all explored within the text but the lasting work was based on Polygon shapes. Birkhoff's theories were never tested against human responses; therefore his theories and application was not tested until Eysenck & Castle's (1970b) paper when the concept of individual differences in aesthetic responses was explored. Eysenck & Castle tested responses to Birkhoff's polygons on large sample (1100 participants) and found very small positive correlations between experience in art and aesthetic preference: correlations of r=.28 for Art trained students, and r=.04 for non art trained students. The impact of individual differences on aesthetic preference has proved a fruitful area of discussion and will be explored in greater depth in later chapters within this thesis.

Eysenck (1916-1997) was a prolific researcher and influential psychologist in the wider area of individual differences in Psychology. Aesthetic responses were the topic of his doctoral thesis, published in 1940 where he attempted to examine both the individual factors that influenced aesthetic experiences, but also to determine if there was a general factor for beauty. Eysenck attempted to take Birkhoff's (1933) formula further by applying a predictive component based on further empirical testing. Focusing on the interplay between complexity or harmony and order or unity, Eysenck derived a predictive formula using a regression equation that he stated could be used to predict preference for simple geometric forms (Eysenck, 1941a). This equation accounted for over 80% of factors influencing preference judgments (Eysenck, 1941b). His results presented an interesting move away from previous research because complexity was found to be a positive predictor of preference, rather than as Birkhoff (1933) describes a factor influencing attentional viewing, which was then rewarded with unity and order producing a hedonic response. As a result of this Eysenck (1968) proposed a simplified formula, whilst highlighting the need much more complex analysis to accommodate different kinds of aesthetic stimulus.

Further investigation allowed simplification of the many of the factors in the original regression equation (1941b). Order was measured by various forms of symmetry (vertical, horizontal and rotational) and the number of sides and presence of angles other than 90° -measured complexity. He later recognised the limitations of his work in applications outside polygons figures but believed that order and complexity and the interaction between the two factors was in need of further investigation as important to understanding aesthetic responses (Eysenck, 1968).

Daniel Berlyne (1924-1976) was interested in general laws of motivation and curiosity (Berlyne, 1974) and he is often cited as the founder of 'new experimental aesthetics' (Martindale, 2007). Unlike Hans Eysenck, Daniel Berlyne opposed the study of individual differences because of a belief that general laws need to be understood before individual differences can be explored (Martindale, 2007).

Berlyne approached the area of aesthetic investigation from a psychobiological stance; methodology akin to Fechner's (1876) bottom-up approach but in addition exploring the physiological effect that stimulus can have on a viewer. Berlyne refers to aesthetic response as based on its 'Arousal Potential' (Berlyne, 1970), which is based on 3 factors the psychophysical properties (the intensity, pitch or brightness of the object/scene), the ecological properties (the signal value and meaningfulness based on the environment) and the collative properties (complexity, novelty, surprise and order). This model is based on the idea that cortisol arousal changes depending on the properties of the aesthetic stimulus being viewed. Initial activation is the non-specific arousal of the reticula activating system, which passes through all the areas of the cortex. Whilst this process is happening, the reticular system fibres pass through pleasure and displeasure centers in the mid-brain. The pleasure center in the mid-brain has a low threshold, as the arousal potential of a stimulus increases, as does our preference. As pleasure centers reach their asymptomatic degree of activation, the displeasure centers become activated and preference begins to decline.

This activation pattern results in the characteristic inverted-U shaped function of Berlyne's theory (Fig 1.3).

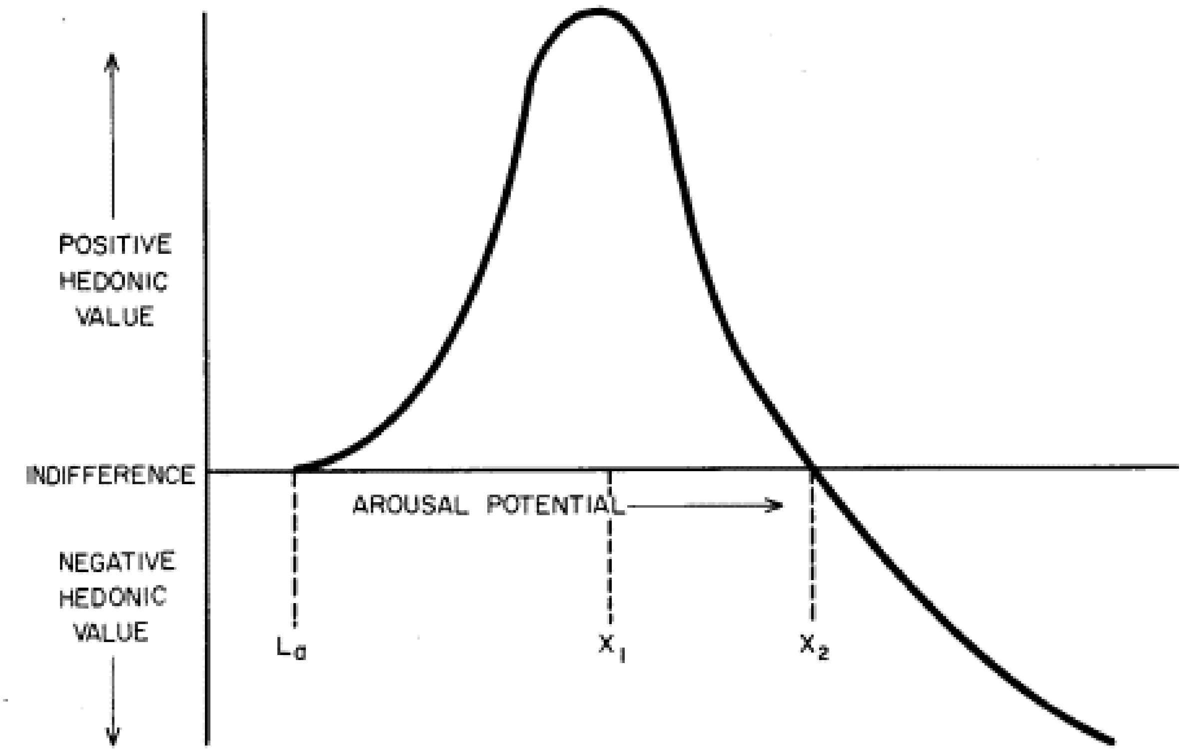

Figure 1.3- Berlyne's (1970) model of aesthetics.

Berlyne (1971) attempted to explain all aesthetic responses with this hedonic law model. This was a key movement in the field and recognised the importance of a number of properties in aesthetic responses as well as inspiring many modern cognitive and neuropsychological approaches with the focus on information processing and cortical arousal.

Unfortunately the simplicity of Berlyne's model means that it is still one of the most frequently cited in empirical aesthetics but also was easily replicable and subsequently disputed with further testing (Martindale, 2007). Martindale, Moore & Bakrim (1990) failed to replicate many of Berlyne's findings, and found that he underestimated 'meaningfulness' on aesthetic judgments. One large flaw in Berlyne's (1970; 71) arousal theory was its inability to differentiate between different stimuli and their arousal potential, according to Berlyne's model if a Monet painting induced a particular level of arousal, and a picture of a disturbing scene or electric shock produces the same level of arousal this will be considered equally preferred. Clearly this is not the case, and here lies the major problem with this unspecified arousal defined in Berlyne's model (Martindale, 2007). It could be argued that the inverted-U shaped function of preference could be useful when used in a group of similar images, as Birkhoff (1933) limited his theory to. This model has been useful in extending the investigation of complexities impact on aesthetic judgments and Berlyne's work continues to inspire the further testing of complexity as a collative variable in aesthetic judgment (Nadal et al, 2010; Forsythe et al, 2011).

Conclusions:

Despite its limitations the Berlyne model of aesthetic preference and the other principle theorists discussed in this section, have had a large impact on the current work in the aesthetic field. To move forward in the field, the foundation needs to be acknowledged and built upon in the aesthetic research following these foundations. Most of the very early research in experimental aesthetics focused on the link between complexity and order in the stimulus and most concluded that this continuum could predict or shape our preferences. The work in this thesis interestingly is still exploring this interplay between complexity and order in stimulus and whilst the ideas have been challenged and tested and new theoretical and quantifiable measures have been taken, the role that complexity plays in preference is still probably one of the largest in the field, even over 100 years since Fechner began this empirical investigation and centuries since aesthetics was first contemplated.

2.0 Modern Perspectives of Psychology and the Science of Aesthetics.

Much of the early research on empirical aesthetics focused on the qualities of an object that contribute to our aesthetic judgments. Whilst many researchers still explore this perceptual processing model of aesthetic judgment there have been many advances in the field of cognition and neuropsychological responses to measure aesthetic response. This chapter looks at increasingly modern theories of aesthetic judgment based on complexity, natural shapes, art and simple patterns. These stimuli offer a framework for exploring the new and advancing theories accounting for preference in the current times. The developing trends in modern aesthetic research will be outlined and explored below to show the pattern of research across the lifespan of empirical aesthetics.

2.1 Overview of approaches in modern aesthetics

Since its early development, the field of experimental aesthetics has received a multiplicity of attention across different subfields in psychology and other disciplines. As the skills and interests of psychologists have diverged so to have advancements in psychological theory and knowledge. New advances in technology have moved forward the scientific exploration of perception. For example, advanced mathematical calculations allow detailed quantification and measurement of previously under researched stimuli because they support more stringent experimental procedures.

In the beginnings of the, field two broad approaches to studying aesthetic responses emerged, objectivism and subjectivism. The objectivist view held that beauty is derived from the object: the features of the object that contribute to our overall assessment of beauty. A subjectivist view held that beauty is derived from the individual and their experiences, emotions and knowledge. Whilst most of today's research do not take an extreme dichotomous stance, it is important to explore the history and approaches previously taken in the field. Despite this a large amount of psychological research is based on objectivist approaches because it enables stringent quantification and examination of the physical factors that contribute to beauty. In other words, there is strong experimental control, but it comes at a trade-off; how ecologically valid it is to compartmentalise aesthetic experience?

2.2 Objectivist/Bottom-up Approaches to Aesthetics

Put most simply, seeing is a neural activity initiated by light reflected from a surface (Solso, 2001). The object we are 'seeing' reflects light, that when it reaches the retina, triggers signals, which are transduced into neural activity. That neural activity is passed along to the brain for additional higher order processing. This view of visual perception is lawful and structured, the processes and physical characteristics of light and neurotransmission follow set rules with little to no variation across individuals. So we are objective in what we see, at least in a physiological sense.

The initial exploration of aesthetic responses as a function of the object or stimulus can be traced back to the early philosophers (Aristotle, Kant, etc.), a perspective that continues in todays modern field of experimental aesthetics. The quest to understand factors that contribute towards our experiences of beauty are still some of the most published findings in the field. Factors such as size, shape, colour and proportion continue to be investigated in new and advancing ways.

There is an emerging wealth of literature exploring the aesthetic preference for symmetry that demonstrates that modern experimental aesthetics still values and attends to the idea that aesthetic preference is a response to the properties of an object, rather than based in more subjective experience. Whether it is human faces or visual patterns, symmetry has been found to be one of the most robust predictors of aesthetic judgments in both humans and other animals (Cárdenas & Harris, 2006; Little et al, 2007;Shepherd & Bar, 2011; Rodrigues et al 2004).

Attempts to understanding this relationship have focused on the biological significance of symmetry. Cádenas & Harris, (2006) believe that the preference is related to ease in processing. In other words, the less energy an organism needs to use to process something, the more aesthetically pleasing it will. These ideas flow from the processing fluency hypothesis (Reber et al., 2004; Winkielman et al 2006). An idea, which attempts to formulate a theoretical model to guide examination of these phenomena, and it is outlined in detail later in this chapter (Section 2.3).

Similarly, the study of colour preferences and aesthetic responses has a tradition, which dates back Cohn (1894) and his study of synaesthesia (the merging of the senses).   Eysenck carried out key studies into this area during his doctoral thesis. He reviewed a large cohort of colour research concluding that a) there is general agreement between colour preferences of all people, b) that alternative saturation results in a bipolar like/dislike response and finally c) that there is very high agreement of preference (0.95) between sexes (Eysenck, 1940). These findings point towards a universal theory of colour preferences, but it appears that individual differences across a range of variables still play a role in explaining some variance across aesthetic preference. McManus and colleagues (1981) revisited the aesthetic theory of colour with additional methodological advances measured some 40 years following Eysenck's exploration. McManus et al (1981) highlight that previous studies of colour preference generally lack any clear experimental definition and design to allow true assumptions to be made. To combat this they adopted more stringent experimental methodology, using Munsell colour patches, accounting for hue, value and chroma. Results indicate that the majority of participants showed preference for blue and dislike for yellow. This effect has been reported across species (Humphrey, 1972; Sahgal & Iversen, 1975), suggesting a potential biological and adaptive function of this colour preference. Further discussions explore the individual differences across colour preferences, with hue appearing to have the most variance across participant groups. McManus et al (1981) are conservative in their conclusions and highlight the need to further exploration of aesthetic response to colour.

Most recently, Stephen Palmer and Karen Schloss of the Berkley Colour Project (BCP) unravelled our aesthetic responses to colour as a function of an object or scene. Pointing towards the work of Eysenck's (1941) and McManus's (1981) Palmer and colleagues report that despite some large individual differences in preference, consistencies for colour exist across groups. Palmer, Schloss & Sammartino (2013) argue that group colour preferences show systematic and reliable patterns of aesthetic preference across the 3 dimensions of colour; hue, saturation and lightness. The highest aesthetic judgments were given to blues and the lowest to yellows. This effect appears stable, but it is difficult to explain from a psychophysical point of view.

The patterns reported by Palmer et al, (2013) are consistent with the Ecological Valence Theory (EVT). EVT is a theory; developed by Palmer & Schloss (2010) following a series of experiments, explored averaged colour preference across group of individuals from different countries, ages and universities. EVT suggests that aesthetic response is directly related to how strongly related associated objects are related to the prototypical colour. This model moves away from a traditional objectivist view as psychophysical research would take and moves towards a more interactionist approach in which both objective and subjective influences play a role in aesthetic judgment. The EVT proposes that people like/dislike colours to the degree they like/dislike the objects they associate with that colour, for example blue is most preferred and associated with positive stimulus such as clear sky, clean water and yellow is least preferred as it is may be associated with negative stimuli such as rooting food and faeces. These findings could suggest that an innate or evolutionary route to preference based in our ancestral history. This assumption along with the associated difficulties in confirming these findings, have possibly contributed to the lack of corroborating studies. Strauss et al., (2012) found that preferences for colours can be affectively/emotively biased but manipulation in priming either positive or negative associations prior to aesthetic response measurement will demonstrate an effect of aesthetic preference alteration. In this study participants were shown either positively valence red images (strawberries and cherries) or negatively valence images (blood and guts). Weighted averages revealed that 80% of variance was accounted for by this affective priming.

Schloss et al., (2011) furthered these findings by finding culturally bound colour preferences based on school colours, with participants showing greater preference for their own school colours over the rival school. Individual differences such as gender, age and culture have also been explored at the BCP. The findings suggest that objective bottom-up processing may influence aesthetic judgments to a certain point at which subjective top-down influences shaped by individual experience take over and govern colour preferences.

Further areas in modern aesthetic research, adopting an objectivist bottom up approach to understanding aesthetic response, include the influence of size, shape and proportion. At first glance, observers prefer large objects to small (Silvera et al., 2002). In contrast to objects with sharp contours, heightened preference has also been reported for objects with curved contours (Bar & Neta, 2006). These responses have since been found to be consistent across both abstract and recognisable objects (Silvia & Barona, 2009) and are stable across valence balancing (Leder et al., 2011). Researchers attributed this to an interpretation of sharp contours as potentially more threatening and harmful than objects with curved edges, recognition of edges and rapid response reactions were essential to early human survival.

Complexity and order have been acknowledged through the history of empirical aesthetics as an important area of investigation. As discussed in the previous chapter, Berlyne (1970) approached responses to complexity from its arousal potential perspective. His approach, exploring motivation and curiosity, argues that arousal is hedonic up to a point before it becomes negatively marked and preference begins to fall. This inverted-U function of preference is largely disproved as a general model of explaining all aesthetic responses (Martindale, 2007). Despite this, there is increasing exploration of Berlyne's (1970) theories within visual complexity. Complexity is an important, and not yet fully explored field within aesthetics and makes up a large component of this thesis. A more thorough examination of visual complexity and aesthetic response will be explored in Chapter 3.

Prototypically or 'supernormal' stimuli have been found to contribute significantly to aesthetic preferences. Ramachandran & Herstien (1999) highlight prototypicality of an object as a predictor of preference, and believe these extreme images excite and simulate the brain as the natural (realistic/normal) images would however because of the extreme nature of features this excitation is experienced more strongly than the original stimulus. Evidence for this 'Peak experience' have been linked with evolutionary theory, as our reactions towards survival are exaggerated and the objective features resulting in these are amplified. This theory could account for the draw of artistic representations over realistic photographs of objects or scenes (and for previously reported colour preferences). Artists appear to have the ability to highlight the principal features and amplify them to a point evoking the highest aesthetic response (Ramachandran & Hirstein, 1999). These findings open potential inquiries about how individual responses can be enhanced using modified or man-made stimulus over real objects or scenes. One such example could be the use of pictures of nature within health care setting which has been found to promote well-being responses (Ulrich, 1991), this 'peak experience' theory could be used to generate images that amplify well-being responses, fractal patterns could be one of the possible methods to do this and will be discussed in depth in subsequent chapters.

A 'direct theory' of perception (Gibson, 1966) or 'bottom-up' processing, stipulates that the visual system processes the world around us as it actually is. A common analogy is that perception resembles a camera through which we as naïve observers experience a given visual situation. All the findings outlined above have roots in this objectivist approach to aesthetic judgment, and researchers continue to regularly adopt this approach to allow further understanding of the physical factors that contribute to aesthetic responses. One consistent finding when exploring the universality of preference for particular bottom-up perceptual processes is the impact of individual differences. Differences in preferences for the factors across have been found across age, gender and other demographic variables and warrants further investigation.

Alternatively, the modern approach to aesthetic research have moved toward a base within the subjectivist perspective, in which beauty is considered as existing in the eye of the beholder. Our subjective experiences shape our preferences and this means that a unified theory of beauty is a challenge to formulate because, whilst the origins of beauty can be explored, subjectivity means that it is difficult using bottom-up measures to make firm and universal predictions about what people will experience as being beautiful. That being said, the acknowledgement that beauty is a subjective experience has permitted researchers to explore the factors that make us different from one another, and how those differences impact on aesthetic experience. So for example, the collective impact of culture and experience takes us to the other end of the continuum, towards a constructivist theory of perception (Gregory, 1970) whereby processing of the visual world is a 'top-down' process influenced by previous experience, emotion and understanding.

2.3 Subjectivist/top-down approaches to aesthetics

Moving away from objectivist approaches which see beauty as an inherent quality of an object, the idea that our experiences can shape our preferences emerged as a new school of thinking. Cognition and perception is at its "*most sophisticated in the cognition and perception of art works*" (Lopes, 1999), because understanding the art perceiving mind is key to understanding human cognition.

A common saying about familiarity is that it breeds contempt (widely attributed to Aesop c620-564 B.C). Aldous Huxley was similarly disparaging when pronouncing that *"familiarity breeds indifference"(1956).* However this is not so for the psychology of aesthetic experience, in fact; *"familiarity may breed contempt in some areas of human behavior, but in the field of social ideas it is the touchstone of acceptability."* (John Galbraith; American Economist in The Affluent Society 1958). A whole higher preference will be shown for scenes and objects that we are familiar with over those, which are new and novel and we call this the mere-exposure effect.

Early discussions of the impact of familiarity can be seen in Fechner's (1876) work, however Zajonc (1968, 1984, 1998) has received the most attention in this regard. Zajonc conducted a series of experiments in which participants were exposed to a variety of different stimuli (Chinese characters, nonsensical words and photographs) and preference ratings demonstrated that merely repeating exposure to a type of stimulus results in increased positive attitude towards stimulus originally rated 'neutral'. This effect increased with further viewing, as long as the stimulus was 'unreinforced' and only accessible in perception rather than conscious processing of the stimuli.

The work on Zajonc has resulted in a large number of replications studies. Exposure effects have been used in a wide variety of research domains. For example, strong mere exposure is found in children for representational art (Bowker & Sawyers, 1988). Hansen & Wanke (2009) found that in marketing research, exposure to a brand name product influenced attitude. Other studies have found the link between exposure and preference in food (Pliner, 1982) and music (Peretz et al, 1998). Cutting (2007) tested the effect with impressionist art in adults; results reflected the mere-exposure effect, with participant demonstrating higher preference for familiar pieces that had received most publication and display. Cutting's study suggested that even passive, unconscious exposure would lead to powerful attitude change. In fact studies has shown that mere-exposure effect is most powerful with implicit rather than explicit awareness of repeated exposure. There is an inverse relationship between stimulus recognition accuracy and the magnitude of the exposure effect across all mere exposure experiments (Bornstein, 1989).

Bornstein's (1989) meta-analysis explored the scope of mere exposure theory and found the effect for abstract paintings and drawings were the weakest. Meaning that in unstructured, unfamiliar images repeated exposure is less likely to increase aesthetic experience. The impact of complexity of the mere-exposure effect highlights an interesting pattern, and makes links to Berlyne's (1979) arousal theories of preference. Complexity is a powerful predictor of preference for a variety of visual stimulus. The impact of repeated exposure of complex images has found repeated exposure results in heightened preference (Saegert & Jellison, 1970) however liking for simple stimuli did not show the same pattern, with results showing a peak in preference following fewer exposures. Forsythe et al (2008) found that familiarity with abstract shapes influences complexity ratings, and participants perceived familiar stimuli as less complex than stimuli that are new and novel.

Tinio and Leder (2009) conducted a series of experiments testing the mere-exposure effect on 2 established and reliable predictors of preference (symmetry and complexity.) Their initial studies exposed participants to abstract patterns and asked them to rate the perceived beauty. Initial results found consensus with original findings that exposure leads to heightened ratings. In a series of additional studies however, Tinio & Leder found that after repeated exposure to complex stimulus, participants held a greater preference for simple patterns, and participants who had been repeatedly exposed to simple patterns held a greater preference for complex patterns. The researchers say this effect is only seen in 'Massive familiarization' and not in 'Moderate familiarization', if we are consciously aware of repeated exposure it appears to have the opposite effect.

This change in preference could be likened to Berlyne's (1971) inverted-U function of novelty. In moderate familiarisation, the image is still familiar but novel enough to keep our interest, however during massive familiarisation, novelty is diminished and the viewers become bored of the stimuli. It appears that there is a delicate balance between preference and familiarity, what could be termed the 'goldilocks effect' with familiarity and complexity needing to be 'just right' to have positive aesthetic responses.

A vast volume of literature supports the mere exposure effect, it has been found to be robust, across gender, age and cultural background (Bornstein, 1988), yielding strong results for a variety of stimuli and using a variety of scales of measurement (Bornstein & D'Agostino, 1992). There is some suggestion that two distinct types of mere-exposure pattern operate; the traditional effect (as outlined above) and the structural mere-exposure effect. Zizak & Reber (2004) made the distinction when they found that the effect can be replicated not only with direct stimulus (i.e. the same stimulus is shown and rated) but also with stimulus that demonstrate underlying rules of structure or patterns. Focusing on artificial grammar (AG is a type of stimulus consisting of letter strings appearing chaotic and nonsensical but with underlying rules that participants are required to learn through the experiment), Zizak & Reber asked participants firstly to classify if the artificial grammar conformed to the principles of the grammar and secondly to rate how much they liked them. The results were influenced by the extent to which participants were exposed to the sentences. At higher levels of familiarity, structural mere exposure occurs, however at moderate familiarity only classic mere exposure occurs. These results suggest an implicit learning theory may be involved in aesthetic judgment, although the potential impact needs further investigation to become clear.

Explaining the mere-exposure hypothesis?

There are a number of theories exploring the reason for the mere exposure effect. Some argue that learning processes underlie the effect (Gorden & Holyoak, 1983) this can take place apparently outside conscious awareness- involving implicit rather than explicit knowledge about a stimulus. This research suggests that not only previously encountered stimuli would evoke heightened responses, but proposes that with repeated exposure we learn implicit patterns that are used (unconsciously) when rating similar stimulus.

Perhaps the strongest, and certainly most supported suggestion, explaining the mere exposure effect see's it as a cognitive process that enables us early recognition and identification; some have used the mere exposure model to explain the effects seen in perceptual/processing fluency models of preference (Bornstein & D'Agostino, 1994). Put simply, we prefer stimulus that we can process with ease, and this ease, which improves with each exposure, results in a heightened (and mostly unconscious) positive hedonic response. The link that perceptual fluency was underlying the effect of mere exposure in heightened aesthetic responses was first introduced by Jacoby & Kelley (1987) and Jacoby & Whitehouse, (1989) who believed positive affect responses felt for familiar scenes and objects was down to a misattribution of perceptual fluency for liking, we demonstrate preference for images that we are able to process with relative ease. This area of research has since been developed and tested using stringent methods and is one of the dominant theories in understanding aesthetic judgment in modern research.

The interactionist approach to aesthetic processing:

The Reber, Schwarz & Winkielman's (2004) theory of processing fluency builds on mere exposure as it explains beauty as a function of the perceivers processing dynamics. The theory stipulates that the easier a scene/object is to process then the higher the positive aesthetic response to the scene. Reber et al's (2004) theory offers one of the most comprehensive theories of aesthetic judgment since its philosophical foundations. The model of processing fluency looks at low-level processing based on the stimulus properties as well as higher-order cognitive processing involved in stimulus recognition and meaning classification.

Simply put, the processing fluency model proposes that the easier we can process stimuli, the more positive an individual's response will be. This model is built on 4 assumptions that account for the position and scope of the model. The first, that objects differ in the fluency in which they can be processed. This assumption is supported by information processing and perceptual studies. The second assumption, that processing fluency is hedonically marked, and high fluency is subjectively experienced as positive has foundations and support from the feeling-as-information models. The third, processing fluency feeds judgment, as people use subjective experience to make judgments and finally the fourth assumption is the impact of fluency is moderated by expectations and attribution (Reber et al., 2004).

Perceptual Processing-Fluency:

A wide range of research has been conducted looking at the factors/properties of stimulus and how these relate to aesthetic judgment. This theory of aesthetic pleasure, unlike many others, does not dismiss the many years of objective research into the qualities of stimulus that influence beauty and aesthetics, but instead it includes metaphysical theory as part of the explanation for preference. Among others, factors such as proportion and balance were identified (Birkhoff, 1933, Fechner, 1876 Gombrich, 1984) with symmetry (Makin et al, 2012), complexity (Berlyne, 1971, Eysenck 1941) as well as clarity and contrast (Gombrich, 1984, Solso, 1997). Processing fluency takes into account these already established theories and houses them under the same umbrella. These elements cumulated into beauty because they improve a perceiver's ability to process the image more quickly, resulting in a heightened aesthetic experience. The properties outlined above aid in ease of processing therefore increasing affective response to the stimulus with these features. Perceptual processing fluency also according to Reber et al (2004) also accounts for increased aesthetic preference for prototypical over non-prototypical stimuli (Martindale, 1984), this is based in findings from cognitive psychology that demonstrate general preferences for 'average' stimulus (Rhodes & Tremewan, 1996). Prototypically is processed more easily than its counterpart, therefore the processing fluency hypothesis can account for these findings.

Complexity: A problem for processing fluency model?

Complex stimuli can be raised as a potential issue with the processing fluency model. We will find the most simple stimulus the most appealing however preference also increases with complexity (Berlyne, 1971, Forsythe et al 2008). How then can this be reconciled? Reber and colleagues (2004) attempt to explain the link between complexity and preference within the processing fluency hypothesis by suggesting salience plays of role in aesthetic processing.

> *"As complexity increases, the salience of the source of perceptual fluency decreases, enhancing the misattribution of fluency to beauty. However, further increases in complexity will eventually reduce processing fluency, leading to decease in perceived beauty. These mechanisms would combine to form a U-shaped relation between complexity and beauty, as predicted and found by Berlyne (1971)."*
>
> (Reber et al., 2004, p. 373)

Biederman, Hilton & Hummel (1991), found that complex shapes often have higher redundancy and thus are recognised faster than simple shapes, therefore suggesting, that simplicity doesn't necessarily mean a stimuli will demonstrate ease of processing. It could be suggested that the conceptual processing fluency, outlined by Reber et al., (2009) may have an equal interaction with aesthetic judgment, as does perceptual processing fluency. It is the interplay between the semantic knowledge and the sensory experience that results in heightened results for complex images.

Fluency in processing hedonically marked?

The feelings-as-information model (Schwarz & Clore, 1983), and more recent findings (see Schwarz & Clore, 2003 for a review), found that our feelings serve as a source of information in their own right. Fluency in processing results in a heightened positive affect and this has been observed in a variety of studies including perceptual priming and psychophysiological measures (Winkeilman & Cacioppo, 2001). As mood is a source of information, this ease in processing involved heightened affective responses, which may lead to heightened aesthetic judgments based on these positive hedonic markers. This could account for the higher preferences found in the perceptual processing fluency account above.

Higher-order Cognitive (Conceptual) Processing Fluency:

The Reber et al., (2004) model also examines the role of higher-order cognitive processes and processing fluency in preference. Taking the top-down, subjectivist point of view, that preferences are individual '*in the eye of the beholder*', this perspective accounts for taste and cultural differences within our aesthetic history. The semantic meaning of stimuli is important, as are our individual experiences and the ability to process new information. This is an added advantage of the processing fluency model because we know that meaningfulness is a strong predictor of preference (Martindale, Moore & Borkum, 1990) suggesting that higher-order cognitive processes may be involved when assessing a variety of visual stimulus. Meaningfulness is a better predictor of aesthetic preference than complexity, and meaningfulness is directly related to the ways in which participants will interact with a stimuli. Hekkert and van Wierngen (1990) found different relationships of preference with abstract and representational art. For abstract art, a Berlyne (1971) inverted-U preference for complexity was found but for representational art, prototypically and preference showed a linear relationship. Prototypically in this case can be said to influence the perceived complexity of an image.

According to the processing fluency model, preferences develop as individuals become exposed to more complex and advanced imagery, thus accounting for expertise related differences. Differences can be found between novice and expert group preference as the different viewers approach the artwork in a fundamentally different way (Winston & Cupchik, 1992). Expert viewers adopt a processing which highlights the challenge of complex works, perhaps because the prototypically or 'structural' similarities are better known to the expert. Novice viewers rely on the personal meaningfulness and familiarity of an artistic stimulus. Similar differences between viewer expertise can be seen in wider research (Cupchik & Gebotys, 1988). The studies discussed above offer support for Reber et al., (2004) model of conceptual processing fluency, they demonstrate the role the individual experience and knowledge, can influence our aesthetic evaluations.

Belke et al., (2010) found evidence of the impact of cognitive fluency in art appreciation, when they studied the impact of bogus titles on artwork. These results supported Reber et al., (2004) in that paintings given semantically related titled were most preferred. The title acted as a conceptual primer to higher-order processing of the image, secondary preferences were shown to ‘no title’ paintings and finally semantically unrelated titles demonstrated the least appreciation, as the mismatched prime increased processing time.

From the objectivist approach we now have a greater understanding of what people find most aesthetically appealing however the subjectivist approach extends this and attempts to unpick the collective impact of culture and experience. This takes us to the other end of the perceptual continuum, towards a constructivist theory of perception (Gregory, 1970) whereby processing of the visual world is a ‘top-down’ process influenced by previous experience, emotion and understanding and preference. Although often examined in isolation, there is a synergy between the two theoretical approaches that can direct and inform stringent empirical research; objectivism supports the analysis of composite parts, whereas subjectivism helps us explore why individuals, cultures or subgroups like what they like. Most modern philosophers and scientists now reject dichotomous thinking advocating a cross-cultural internationalist position of aesthetic perception (see for example Reber et al., 2004).

Can you be more subjectively exact about what you see? This is perhaps somewhat of an oversimplification, but how is it possible to objectively measure subjective experience? The use of cognitive and/or neural mechanisms in aesthetic judgments links with the newest school of thought in aesthetics research, neuroaesthetics. These approaches will be discussed in this section to give the reader an overview of the modern approaches to aesthetic research in psychology.

2.4 Neuroaesthetics: The present and future in the field

In 1999 Semir Zeki introduced the term 'neuroaesthetics', offering a unified name to the newly emerging scientific exploration returning to the biological underpinnings of aesthetic experience. Of course, the identification that perhaps our aesthetic responses and behaviour are innately formed can be traced back to early philosophical and scientific musings (see Chapter 1), however with the power of a unified name, and key advancements in technology, neuroaesthetics spurred the field of empirical aesthetics into new and unexplored horizons.

Neuroaesthetics is a field of study which adopts neuroscientific methods such as: functional MRI (fMRI), Positiron emission tomography (PET), magnetoencepholography (MEG), Electroencephalography (EEG) to study preference, appraisal and aesthetic judgment. There are in general 3 distinct but related fields of research within neuroaesthetics. Firstly a striving to understand the logic of universal truth to aesthetics; this area looks at art (as well as other stimuli) and attempts to unpick aesthetic laws that provoke aesthetic responses. Secondly, research attempt to find the relationship between neurological and psychological processes by exploring the brain responses to art and aesthetic stimuli. The final thread, currently, in the field of neuroaesthetics would be the evolutionary foundation of aesthetic experience. As the approach is centred on the biological underpinnings of aesthetic experience, it is important to understand the evolutionary rationale for aesthetics as a process and stimuli response. The following section will discuss the progression through each area, and outline main findings. Finally it will explore the potential issues facing neuroaesthetics as a field and lay the foundation for the current research strands within this thesis.

Universal Truths to aesthetics:

Early research into the field of neuroaesthetics focused on understanding the laws used by artists, both intentionally and unintentionally to create illusions of reality and evoke aesthetic responses. Ramanchandran & Hirstein (1999) developed 8 laws of aesthetics commonly found in art across different cultures and used to optimise and titillate the visual experiences of the viewer and the artists themselves. Each law is established on the biological underpinnings of preference from an evolutionary standpoint.

One such example is the use of 'supernormal' stimuli within art, in which the artist emphasises or caricatures the stimulus. Examples of this can be seen in the colour palates used by Van Gogh (Fig. 2.1), his use of extremes to colour his landscape would, according to this model, be preferred over Constable's more muted and natural colour palate (Fig 2.2). Ramachandran & Hirstein (1999), believe that the extremes of supernormal images excite the same areas of the brain as the natural examples would, however this excitation is stronger in supernormal stimuli.

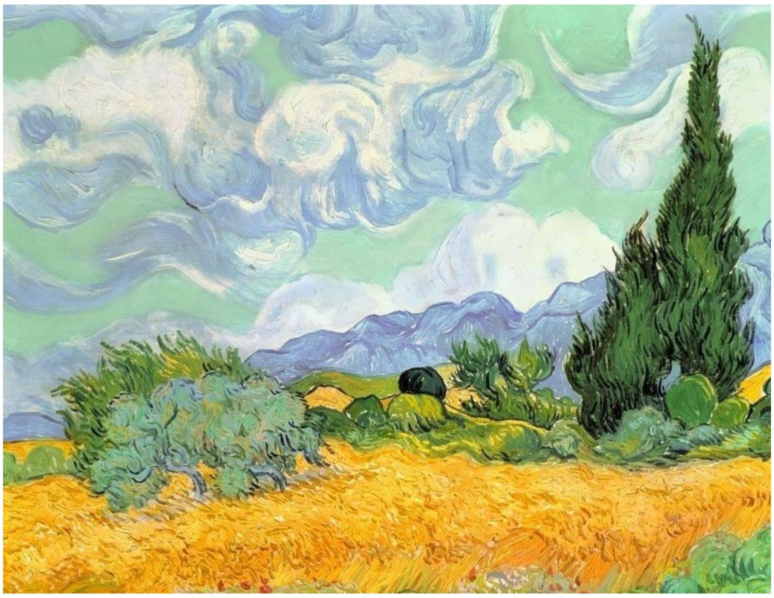

Figure 2.1- Van Gogh- Wheatfield with Cypresses- 1889

Figure 2.2- Constable- Fen Lane, East Bersholt 1817

Some argue that aesthetics is a by-product of basic evolutionary instincts and art, as a stimulus, can be seen as a 'peak experience' of these occurrences (Pinker; 1997, 2002) but this suggestion does not account for the powerful and as Kant would put it 'sublime' experiences of nature that appear to have a universal and powerful aesthetic effect.

Semir Zeki's (1999) book *"Inner Vision"* argues that artists are in a sense neurologists, he goes on to say that when we say something is pleasing, what we are truly saying is that it pleases the brain. Artists appear to have the ability to understand and harness this knowledge in the creative process. Neuro-imaging studies present some support for this idea. Lengger et al., (2007) found significantly higher levels of activation in the left frontal lobe and bilaterally in the temporal lobes when observers were examining artworks. Representative artworks evoked more associations across different brain areas, with a strong activation of multimodal association areas in the temporal lobe. Other researchers have reported on the activation of reward centres within the brain (Maffei & Fiorentini, 1998) and more have argued that aesthetic experience is a reward because it involves problem solving and the resolution of perceptual problems is self-rewarding (Ramachandran & Hirsten, 1999) demonstrating ties between neuroaesthetics approaches and Reber at al's (2004) processing fluency hypothesis discussed previously.

Exploring neurological responses to art and aesthetic stimuli:

As well as the universal rules of art and aesthetic stimuli, the field of neuroaesthetics has interest in exploring the responses to art and aesthetic stimuli. Chatterjee (2010) provided an early overview of the field of neuroaesthetics and in a more recent review Nadal (2013) summarised the main insights from neuroimaging for the experience of art. Both authors outline the growing evidence points towards an interaction between multiple cognitive and affective processes, and highlights increasingly advanced neuroscientic techniques as a method from which these processes can be understood. The author outlines the two main methods to answer questions regarding the multicomponent experience of art from a neurological perspective are firstly analysing the effect of neurodegeneration or lesions have on aesthetic responses to art and secondly the use of neuroimaging techniques to measure activity in the brain when experiencing/viewing artwork. Below a brief summary of the main findings will be explored to provide an up to date and clear account of current directions in the field of empirical aesthetics.

When exploring the responses from the brain towards artistic and aesthetic stimulus, we can employ established techniques to investigate neurological function based on a variety of states. One such method is looking at differences based on neurological disease or impaired neurological function and how aesthetic and artistic responses differ from 'normal' ageing or functioning population. There is a surprising wealth of case study evidence linking neurological disorders and art production (Zaidel, 2005). Frontal Temporal Dementia (FTD) is one such disorder that has been linked to increased art activity, and findings have shown people with FTD develop susceptibility towards increased art production (Miller & Hou, 2004). Other studies demonstrate obsessive artistic practices in individuals diagnosed with Parkinson's disease following dopamine agonist treatment (Chatterjee et al., 2006). Further studies have shown that damage to the specific areas of the brain including the amygdala have shown the link between these areas and artistic appreciation linked with particularly in the case studies reported with valence (Adolphs & Tranel, 1999; Gosselin et al, 2007) Chatterjee (2010; 2006; 2009) believes this paradoxical response of heightened aesthetic/artistic activity, with reduced neurological functioning in individuals with neurological impairment could be a results of obsessive compulsive features within the disorder, or a response to enhanced visual and expressive vocabulary in the face of verbal or other cognitive diminishment seen in neurological disease. Nadal (2013) however adds words of caution when making claims of neurological link to aesthetic experience and points out that by their nature, exploring neurodegeneration or lesion damage in artistic activity and appreciation is anecdotal and conclusions can only be drawn tentatively.

Responses to artists work with neurological impairment have been reviewed and findings appear to depend of the severity of the disorder and increased artistic acclaim. Zaimov, Kitov & Kolev (1969) reviewed products of 25 artists following stroke and found in some cases the work following was considered as notably different with previously unmasked artistic potential. Further experimental evidence has shown that preferences for artist work changes (among other factors) as a result of Alzheimer's disease with participants, naïve to the hypothesis, rating paintings with increased positive aesthetic response (Williams., 2012 Doctoral Thesis), the work explored differences in preference and complexity responses the 'early' and 'late' style from William DeKooning's artwork, results found higher preference for DeKooning 'late' style works, furthermore these differences do not appear to be a result of differences in visual complexity of the art works. In a bid to overcome some of the problems associated with making claims about the damaged brain regions and aesthetic responses Bromberger et al (2011) adopted a design to explore how much specific brain lesions impair the aesthetic response to art, their findings mark a step forward in standardising the field and show that patients with right frontal, parietal and lateral temporal cortices damage differed significant in aesthetic responses compared with health participants when rating across a number of conceptual scales.

The field of neuroaesthetics goes beyond using purely behavioural measures of preference and with advancements in technology; there has been an increased use of computational equipment to measure the neural correlates of implicit aesthetic judgments of beauty. Nadal (2013) and Chatterjee (2010) both champion the advances in neuroimages techniques on healthy participants to explore the brain activity involved in the complex process of art appreciation. Evidence suggests that at least three functionally distinct brain regions are associated with the experience of art. The first, evaluative judgment, attentional processing and memory retrieval associated with the pre-frontal parietal, temporal cortical regions. The rewards circuit associated with cortical and subcortical regions and finally the low, id and high-level cortical sensory regions (Nadal, 2013).

Previously studies in the field attempted to find the (one) area of the brain associated with aesthetic processes, however results revealed differences in areas of activation in a range of studies, using differing methods and stimuli for investigation. It was proposed by Nadal et al (2008) that lack of specific activation in one region is compatible with the general model of neural processing, linking response to aesthetic stimulus to the more general activation systems involved in reward, decision-making and visual processing (Chatterjee, 2004b; Chatterjee, 2010). Newer evidence supports these claims, that there is no localised area in the brain specialised in experiencing art (Nadal, 2013) instead a range of activity is demonstrated in viewing art which suggests the processes involved in art appreciated are made up of crucial processes involved in perceiving and making decisions in everyday situations. Broadly speaking the perceptual, cognitive and affective systems are involved in the parallel processing involved artistic appreciation and Chatterjee & Vartanian's (2014) review adds support these claims. The authors also suggest that aesthetic processing is found across a number of regions, and propose that aesthetic experiences are emerging from interactions across a number of neural systems specifically the sensory-motor, the emotional-valuation and the meaning-knowledge. The biological bases of aesthetic processing offer one way to work across disciplines, to understand human behaviour; relevant not only to artistic appreciation but wider evaluative aesthetics experiences we navigate through daily.

Evolutionary Theory:

The final area key to the field of neuroaesthetics and more widely aesthetics in general involves the underlying deep biological coding of responses that may point to evolutionary foundation in responses to aesthetics and other stimuli. Whilst evolutionary and biological foundations have been explored in other areas within aesthetics as a field, neuroaesthetics has begun to demonstrate finding that support the notion empirically. Chatterjee (2010) outlines 3 distinct approaches in the framework of evolutionary aesthetics; beauty serves as a proxy for health and mate selection, objects that are beautiful are complex but are able to be processed proficiently and finally that art-making points to an important ritual in social cohesion. The first two approaches are of distinct importance within the current thesis and will be discussed further in chapter 5.

There is growing wealth of evidence demonstrating that beauty standards are not acquired through experience, but are instead a result if innate beauty detectors come from facial attractiveness studies (Langlois et al., 1990). Charles Darwin, in the *Descent of Man* (1871) argued that aesthetic responses have "*been developed through sexual selection for the adornment of some male animals*" (p.99) but other suggest that survival instincts offer a better rationale behind responses to stimuli such as art and most notably landscape. For example many features of the most celebrated art and landscapes have distinctive qualities that mimic the savannah on which human developed and thrived (Dutton, 2010).

Despite its contributions to understanding further the underlying biology to aesthetic responses and activities, the field has been scrutinised and several limitations have been flagged both by its supporters and its critics.

Potential pitfalls of the Neuroaesthetics approach:

John Hyman (2008) has criticised the neuroaesthetics movement for their ill-defined methodology and poorly supported claims. In discussing Ramachandran's work, Hyman (2008) reviews the overall application of his theories to the wider field of art. Whilst acknowledging the empirical support to Ramachandran's peak-shift theory, in which preferences are formed form art as they are exaggerated examples of visually appealing shapes, colours or scenes, he disputes its ability to explain all art and this lack of focus on general art, and more focus, it would seem, on erotic caricatures of the human form. In discussing Zeki's work, Hyman recognises the importance of the link between brain function and aesthetic experience, however he notes that although we can infer from brain activity that an object or element has been recognised or processed visually, this does not offer an explanation as to how this painting or element would elicit a pleasing or emotional response from the viewer. Zeki argues that aesthetic theories will only become intelligible and profound once based on the workings of the brain, but is this truly all we need to understand to explain the complexities in experiencing a piece of art or a beautiful scene.

These empirical theories offer only a glimpse into the many facets of art and studying in the field of aesthetics, and although a few select examples are used, neuroaesthetics is yet to offer a universal theory or art, which encompasses each form. Hyman urges the 'neuroaestheticians' not to ignore the past, the groundwork into aesthetics set out by the philosophers and artists whose domain it has been for centuries. Instead of bursting into a new field with a paradigm shifting theory as a neuroscientist, be acutely aware that these ideas have been considered in the past and the best new theory as well as looking forward will also not disregard the past.

Whilst the field of neuroaesthetics has already offered insight into the neural underpinnings of aesthetic experience, particularly art, there are limitations and restrictions in the field, which are highlighted by Chatterjee (2010), Nadal (2013) and Chatterjee & Vartanian (2014). There is a need for a full understanding of the behavioural responses to aesthetic stimulus before moving on to more advance investigation of the associated neural activity. To avoid problems of reverse inference in neuroaesthetics (Poldrack, 2006) the current thesis uses more traditional models from empirical aesthetics to build a foundation of the behavioural and psychophysical responses to a relatively new understanding of our environment (fractals) with the hope that once the behavioural response is understood the 'internal' psychophysical structures and processes can be explored in an informed way (Chatterjee, 2010).

2.5 Conclusions and summary of recent trends in aesthetics:

This section has given a wide overview of the current approaches and trends in the study of experimental aesthetics. We can see a movement away from a purely objectivist approach as seen in early aesthetics research searching for a physical quality of objects as contributing to aesthetic responses towards a more subjective approach in which personal experience and individual differences contribute to our aesthetics response. This approach outlined by philosophers, as the reason a true psychological science of aesthetics cannot be adequately formed have began to emerge as an important dimension to explore in aesthetics. The future trends in aesthetics research have been considered within neuroaesthetics; a field in which advanced analytic techniques are beginning to shed light onto areas once considered impossible to study quantitatively. It is evident that particular areas of aesthetic research remain inadequately addressed and the search to fully understand each facet of preference is still incomplete. Complexity is on such area that is still discussed commonly in research, but it appears that there are persist issues in quantifying and classifying its impact on preference. The impact of the natural world on preferences has also begun to emerge as an important theme, which requires further attention. The understanding of our aesthetic relationship with nature and natural shapes could help us understand individual attitudes towards aesthetic objects and environments.

The approach adopted by this thesis is interactionist. Complexity and fractal dimension (the main focus of this thesis and discussed in depth in following chapters) will be explored from an objectivist viewpoint in an attempt to understand if universal trends of preference exist in this domain. Subjective approaches will also be employed which explore the impact of experience and environment on preferences for fractal patterns. Individual differences have been seen across a variety of factors and the impact of these will be explored in following chapters.

Whilst the present research does not currently adopt any advanced neuroaesthetics methods, it is hoped that understanding the basic concepts and responses to these fractal patterns can form a foundation from which to explore the associated neural responses in the future.

The following chapter will explore the main topic of this thesis. As we have seen complexity was in the foundation of the field and still to this day is elusive in its relationship with preference. The vast wealth of literature on complexity shall be discussed and fractal dimension is introduced and explored alongside this, offering a new and novel way to characterise the complexity found in many natural shapes.

3.0 Visual Complexity & Fractal Dimension: Measures of Predicting Aesthetics Judgments

The following chapter focuses on one of the main areas of investigation within this thesis, visual complexity as a multidimensional construct. It explores definitions of visual complexity, current methods of measurement and it's link with aesthetic response. The chapter then introduces the concept of fractal dimension, as a new method of quantifying the complexity of nature. The power of aesthetic draw of fractal patterns will be discussed. Finally the chapter highlights the limitations and gaps within the research and discusses how the current thesis will fill these with additional exploration.

3.1 Visual Complexity:

The following section will explore the key area of this thesis exploration. Complexity as evident throughout previous discussions is a key variable in understanding aesthetic experience. Complex information dominates our everyday visual experiences. Perceived visual complexity is made up from both subjective factors, accounting for individual differences across age, culture and environment. For example, familiarity with content has been found to contribute to our overall perception of the visual complexity of a scene or object (Forsythe et al., 2010). As well as objective factors, which relate to the physical qualities and properties of an image, contribute to overall perceived complexity, but a true measurement of these qualities has often evaded researchers. Enhanced statistical and quantitative measurement techniques now permits a more empirical approach to understanding our visual relationship with complexity and this section will provide an overview of these advancements.

By its very nature, visual complexity is difficult to design and evaluate. As outlined above, the perceived complexity of a stimulus can be determined in two major ways. The subjective complexity; based on an individual viewer's experience and the objective complexity; based on physical properties of the images that result in an overall visually complex scene. Visual complexity has been associated with aesthetic responses to a variety of stimuli since the early developments in the field of empirical aesthetics (see Chapter 1) and despite its links, the field faces continued issues with the ability to offer a consistent measure and definition of visual complexity. Armheim (1966) believed in landscape design, that high aesthetic appeal was a result of high levels of both complexity and order. Gombrich (1979) extended this opinion by stating that aesthetic appeal lay at the mid-point between complete monotony and total intelligible chaos. Researchers argue that approaching complexity from either end of the objective-subjective continuum is reductionist and push for a more holistic view of visual complexity. Others believe that complexity is a multidimensional property, which has yet to be adequately operationalized because of the broadness of the topic. A summary of these viewpoints will also be explored in the following section as well as leading the reader to an area of most interest to this thesis, fractal dimension, and exploring how both visual complexity and fractal dimension could be used to further understand our visual relationship to the world around us.

3.1.1 Subjective approaches to visual complexity:

Daniel Berlyne, (as explored in chapter 1) outlined complexity as one collative variable contributing to aesthetic experience. He believed that perceptions of complexity are based upon the arousal potential in individual experience, therefore experiences of visual complexity were a subjective measure and lay in the 'eye of the beholder' rather than any property of the stimulus.

Berlyne (1970) proposed an inverted U-shaped relationship between complexity and preference, his psychobiological approach argued that an optimal level of arousal was preferred and that, depending on the current arousal state of the viewer this could be higher or lower (see Fig 3.1 below).

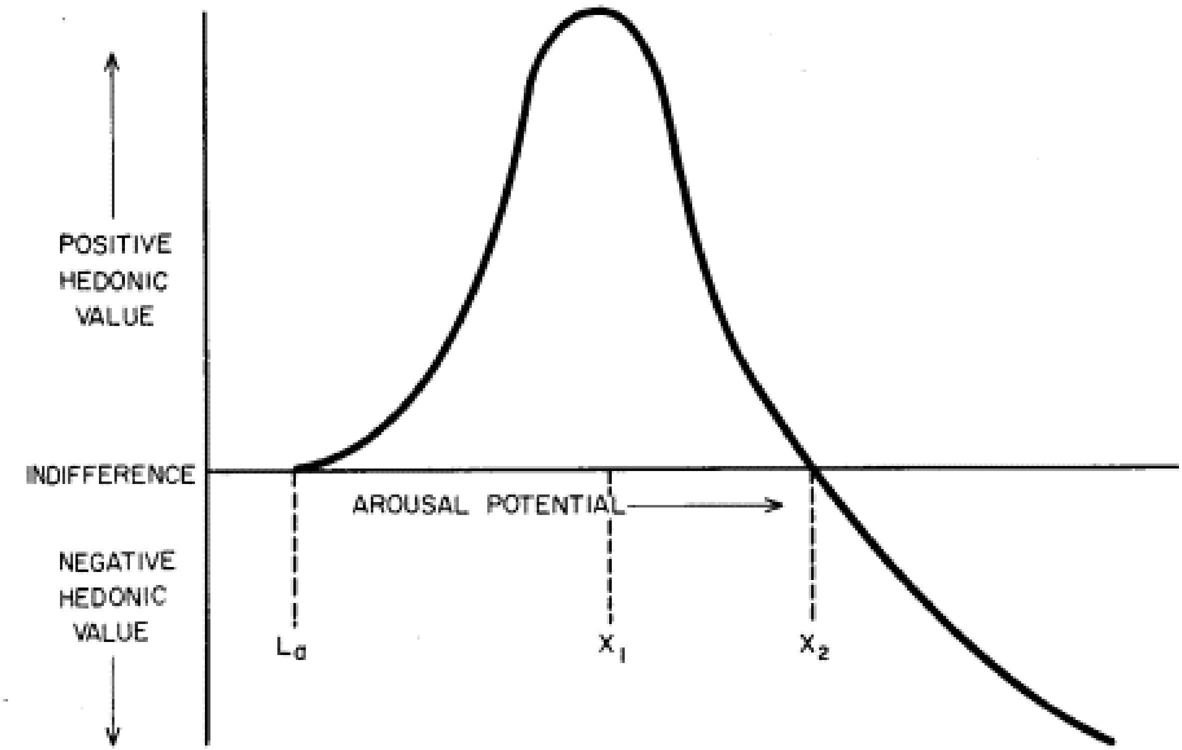

Figure 3.1- Berlyne's (1970) psychobiological model of aesthetics.

The Gestalt approach emphasises the importance of the holistic process in perceptual processing in which factors that contribute to overall complexity of an image do not simply reside within it (Pomerantz & Kubovy, 1981) in which experiences of visual complexity are instead a complex interplay between objective measures and subjective experience.

Familiarity, for example, contributes to perceived visual complexity, suggesting that individual experience with a scene or object would result in even complex scenes being perceived as less complex on subsequent viewing. Vitz (1962) found evidence to support this claim, participants were asked to rate and rank the complexity of black line drawings of 'random walks' with increasing complexity incrementally by adding additional steps from the previous image. The results supported the curvilinear relationship between complexity and preference, with the highest preference shown for images from the mid-range of complexity. Vitz (1962) highlights the role that familiarity plays in preference for complex images. On ranking the complex images for a second time, participants demonstrated higher preference for more complex images demonstrating a peak shift in preference demonstrating the influence of repeated exposure on complexity preference. The role that learning and familiarity plays in perceived complexity was later confirmed by Forsythe et al (2008). In their studies exploring perceived complexity for nonsense shapes, significant interaction effects were reported for training and familiarity. Familiarity appears to bias subjective complexity towards basic level visual processing. These findings call into question the role of human judgments in picture research. Subjective ratings are an established method by which to produce normative data for language, neurological and picture research (see Proctor & Vu 1990, for a review) however Forsythe et al., (2008) demonstrated that such measures were confounded with familiarity for the stimuli.

Supplementary information and learning experiences influence aesthetic judgments in for example including titles for artwork has been found to contribute to preference (Dearden, 1984; Frois & Eysenck, 1995), it is proposed that titles have a particular the impact of cognitive fluency in art appreciation. Belke et al., (2010) studied the impact of bogus titles on perceptions of artwork, findings demonstrate semantically related titles were most preferred, followed by no-title and artwork with unrelated titles was considered least aesthetically appealing. The results suggest that cognitive fluency in processing is facilitated by subjective judgments of aesthetic appeal, naming and semantic content contribute to rating for visual complexity in a scene.

3.1.2 Objective Approaches to Visual Complexity:

To address the extraneous influence of other variables, psychologists and researchers have attempted to formalise the measurement of complexity, arguing that if it were not possible to measure complexity and make predictions from those measures, then how could we every really know what was simple or truly complex?

Gestalt theory was among the first to explore the systematic processes of perception (Hochberg, 1968). The Gestalt movement was a direct response to the structuralism movement within perceptual research and believe that the process of seeing was more than the individual components of shapes, light and colour but instead it was the consistency within the shape, the patterns that contributed to the overall perceived qualities, including complexity, of the object or scenes. Whilst Gestalt theorist found ‘rules’ of understanding perception, they saw the measurement of precise elements of a visual scene to determine response was irrelevant as perceptual systems saw the whole rather than its parts. Fred Attneave (1957) is a seminal figure in this area, explored the different stimulus properties that contribute to subjective judgments of complexity in non-representational figures, he found that it is not simply the case of that the amount of information contained within a stimulus, determined its subjective complexity ratings. Subjective judgment of complexity involve, according to Attneave, more than a sum of its part- a idea aligned with the Gestalt theory of visual perception.

Further attempts to capture and measure objective complexity has been explored through measuring the number of elements; number of turns or amount of symmetry within a stimulus (Chipman, 1977; Hall, 1969) but with recent technological advances came a new fast ways to quantify complexity. Image compression in particular has been found to give accurate objective measures, which correlate with human judgments of complexity (Forsythe et al, 2008). Compression techniques such as Gif or Jpeg seem to be particularly useful in providing a measure of visual complexity that is unbiased from judgments of familiarity

Computational compression techniques were considered a successful method of predicting subjective complexity because of the links with basic information processing theory (Donderi, 2006). Grounded in information theory, when a picture is compressed the string of numbers that represent the organisation of that picture is a measure of its information content (Donderi, 2006). When the image contains few elements or is more homogenous in design, there are few message alternatives and as such the file string contains mostly numbers to be repeated. A more complex picture will have more image elements and these elements will be less predictable. The file string will be longer and contain an increasing number of alternatives. Such measures have demonstrated their usefulness in understanding how humans process visual complexity in an image, in particular demonstrating that familiarity can bias judgements of complexity. In contrast to controls, observers trained to respond to nonsense shapes, rate these shapes as physically simpler (Forsythe et al., 2008). Automated measures have also extended our understanding of the relationship between complexity and beauty In contrast to Berlyne’s findings, when computerised measures of visual complexity are substituted for human ratings of complexity the relationship between visual complexity and beauty is more linear than demonstrated with the inverted U-shaped preference synonymous with Berlyne’s theories (Forsythe et al., 2011).

Despite the wealth of current findings, there is still little consensus about what complexity is and how it should be defined and measured (Forsythe, 2009). This thesis will attempt to take steps to allow closer inspection and tighter definitions of visual complexity in relation to aesthetic response.

3.1.3 Applications of visual complexity:

The research reviewed above, as well as contributions to the knowledge of general perceptual and aesthetic theories, has been used in a variety of applications as we learn more about our responses to visual complexity these theories can be explored and considered in a real world domain. Most prominent in the modern field are measures to aid in website design and aesthetic appeal. Michailidou, Harper & Bechhofer (2008) explored the link between the visual complexity of web pages and the influences this has on aesthetic perception. They suggested that by understanding the complexity and aesthetic perception of a webpage they could infer the cognitive effort required for interaction with that page, others have found that the aesthetic response to webpages are formed quickly that these measures indirectly influence attitude towards webpages (Trachtinsky et al., 2006). Michaildou and colleagues (2008) results found that visual complexity is negatively related with user perceived organisation, clarity and beauty of the page. It is important to explore the factors that contribute to website aesthetics as links have been found between page aesthetics and the credibility judgments formed by visitors in the first few seconds of viewing the page (Robins & Holmes, 2008). This research demonstrates, in a small way, the applications of visual complexity in design, it is important to optimise aesthetic responses in design, however this needs to be based on the principles and findings of the field as a whole.

3.1.4 Environmental Psychology and Visual Complexity:

Heath, Smith & Lim (2000) in exploring the effect of visual complexity of preferences for urban skylines found that silhouette complexity was the strongest influence on preference, arousal and pleasure. This work and the work of Stamps (1991) demonstrate the potential to understand our relationship with our environment in further depth by exploring individual factors within it, such as perceived/measured visual complexity. The results show the potential for using perceptual findings such as these and applying them in design practice to evoke particular responses, namely high aesthetic evaluation. These are limited however to the man-made environments in which we spend time and does not explore the impact of complexity of natural rural environments alongside urban scenes.

Kaplan, Kaplan & Wendt (1972) studied the relationship between complexity and preferences for physical environment. They used a series of photographic slides of both natural and urban scenes that were rated for both preference and complexity. Their work followed Wohlwill's (1968) study exploring complexity as a determinant of preference for various examples of the physical environment with additional and stimulus.

These studies demonstrate the ways complexity can be used to assess the visual environment and predict responses and will be explored in greater depth in subsequent sections. As Wohlwill (1970) concludes, the series of studies demonstrate that responses to slides (photographs) of the environment vary as a function of the judged complexity in the same way to artificially constructed stimuli. Given this, the findings from the studies apply with a variety of stimulus can be used to build a wider picture of responses to physical landscapes.

3.1.5 Defining and measuring complexity; Can it be done?

There is a vast amount of research on visual complexity and its links to aesthetic experience. One issue the field faces is the inconsistency of stimulus used to explore the relationship between complexity and visual experience. As outlined in the above discussions, some studies use computer or hand generated stimulus, which increases in complexity by the number of objects, amounts of turns, or presence of symmetry. Others use photographs or nature, art or websites to explore responses to complexity in a more ecologically applicable way. There are a wide variety of approaches with which to gather complexity ratings or rankings from stimulus. Whilst some employ human judgments others have attempted to develop advanced quantitative measures to provide this information, as with computational compression techniques.

The lack on consistency in what it is to be complex in a stimulus means that the field cannot move forward in a unified way. Some argue that complexity as one concept does not exist, and instead we need to explore it as a multidimensional construct, that many different sub-sectors of complexity exist instead of one overarching definition (Forsythe et al., 2010). This is much akin to the early attempts to define and measure psychology as a field. Its true potential was not fully met until it was divided into a number of subsections, which allowed an adequate depth of analysis and exploration of the topic to take place. Rump (1968) took this multidimensional viewpoint and believed that ratings for a general complexity score were meaningless without further unravelling of the concept. Marcos Nadal's (2007) doctoral thesis conclusions also provide additional support for this theory, his findings outline 3 primary aspects associated with overall complexity ratings and beauty scores. These were, the number and variety of elements, asymmetry and the recognition of individual objects and scenes. These results point to visual complexity as a multidimensional construct with underlying factors requiring further exploration.

As outlined above, complexity has a long past in the field of empirical aesthetics. With advances in technology and analytic techniques there is continued growth towards new ways and avenues from which to study visual complexity and its potential impact on aesthetic evaluation. Despite its long history, there continue to be limitations and issues with current methods used to quantify and measure responses to complexity. Should we, as done in the past, attempt to separate the concept of complexity into finer more manageable areas for a closer measurement, or should we continue to explore the high order neural processes involved in aesthetic judgments as the current directions of neuroaesthetics is taking us? It could be suggested that using new sophisticated methods from neuroaesthetics has helped shed light on historical questions within aesthetics however they contribute little to new concepts without established and prior research evidence to guide studies and analysis. Fractal dimension is one such measure that could be used to further understand visual complexity particularly in a natural environment. This thesis aims to explore and validate established theories of complexity and fractal preference, supporting these with additional evidence and laying the groundwork for future neuroaesthetics investigations into our aesthetic relationship with complex patterns.

3.2 Fractal Geometry: a new measure of the complexity of nature?

The following section introduces the concept of fractals. A fractal pattern is a rough complex shape that can be found in nature, in art and even in physiological structures in the human body. Fractal dimension offers a new method of quantifying many patterns we see in the natural world, that were once considered too 'messy' to follow any statistical qualities. This ability to quantify natural patterns enables further perceptual research to take place to explore our responses, some of which is explored below. Current findings demonstrate an innate response to fractal patterns displayed in both aesthetic judgments, wellbeing and restorative responses. The field still in its youth and current findings are limited, invalidated but promising. The chapter aims to show how this thesis aims to contribute to the field of empirical aesthetics using fractal dimension as a method to study human responses to environmental features. The links to visual complexity are clear throughout, and it is hypothesised that fractal dimension could offer a new method to unpick the concept as a whole. Visual complexity has associated definition and methodological issues and it is proposed that fractal geometry could allow us to define and quantify the visual complexity of the natural world.

A Fractal is a rough complex shape that has had success in quantifying many shapes and processes in nature, which were previously considered chaotic and without pattern. Fractal geometry offers a language by which to describe shapes which cannot be understood by Euclidean geometry alone as "*Clouds are not spheres, mountains are not cones, coastlines are not circles, and bark is not smooth, nor does lightening travel in a straight line*" (Mandelbrot, 1983) this assertion is in contrast to previous views that nature was made up of messy and rough Euclidean shapes. Cezanne's view opposed this; he believed that everything in nature could be viewed in terms of cones, cylinders and spheres, all simple Euclidean geometry. Despite his thinking, Cezanne manages to capture the complexity and fractal properties of nature (Fig 3.2).

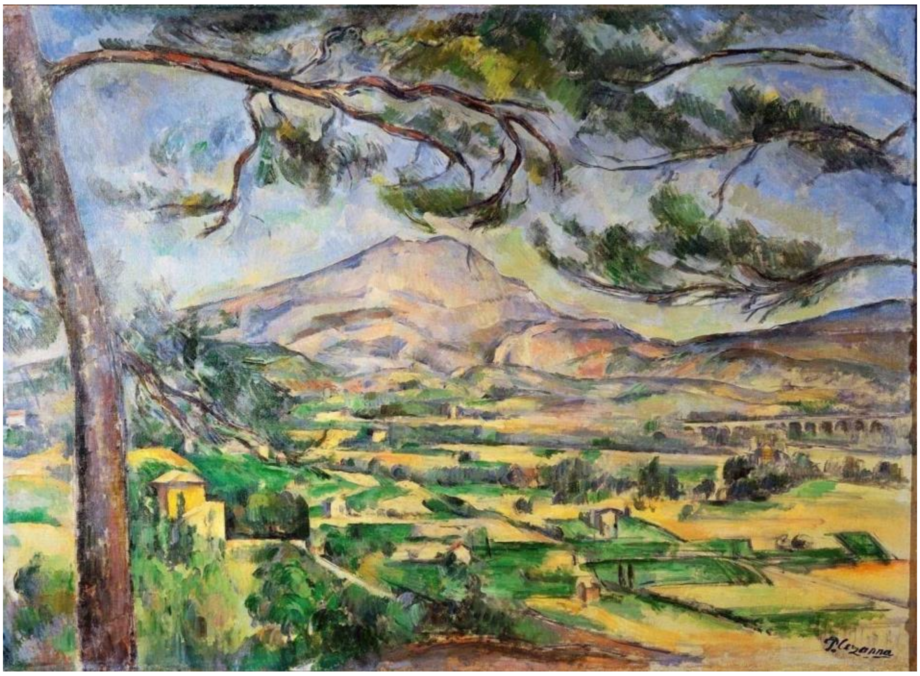

Figure 3.2 - Mont Sainte Victoire (Courtauld) (c. 1887) Paul Cezanne

This ‘knowing without knowledge’ demonstrates a trend in fractals; humans have been surrounded by fractals our whole lifetime and evolutionary history, fractal patterns and processes even make up much of our physiological structure. The ideas have been seen and discussed by a variety of disciplines however despite a few who advocate the field, fractal geometry has not yet become mainstream over more widely known and acknowledged Euclidean geometry. Benoit Mandelbrot (Fig 3.3), the father in the field worked in a interdisciplinary way his entire career, contributing to math, physics, economics and psychology but when pressed he referred to himself as a ‘story-teller’ (Frame, 2013 TedxYale) and passed away during the early years of this thesis so in his memory the next sections with explore the story of fractals so far and in particular the ‘story’ of how fractal geometry has been and can be used to shed light on aesthetics experiences and interaction with the environment.

3.2.1 A Brief History of Fractal Geometry:

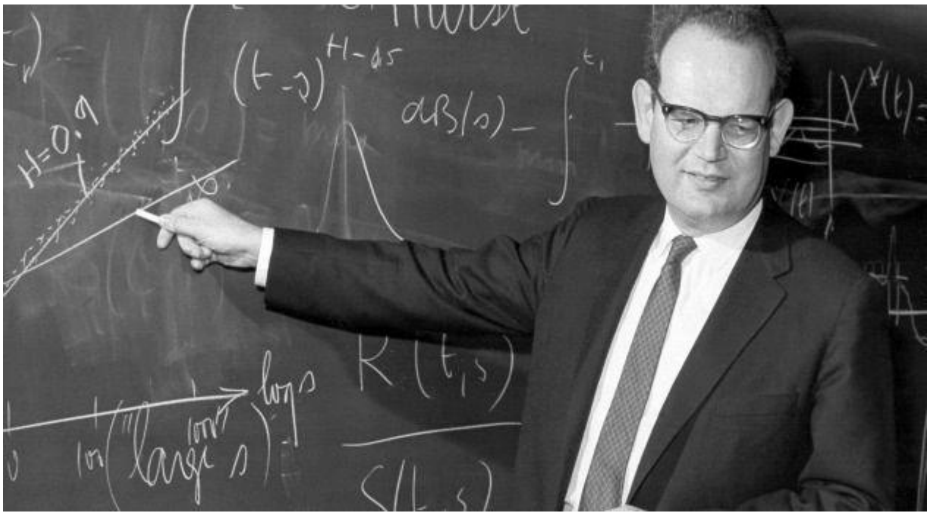

Figure 3.3- Benoit Mandelbrot

Benoit Mandelbrot coined the term Fractal in 1975 after the Latin ‘Fractus’ meaning fractured or broken. He wanted to be able to measure the things that he saw all around him in nature, things that he found that Euclidean geometry was generally unable to measure and describe adequately.

The birth of fractals is often considered to be the publication of “How long is the coastline of Britain?” (Mandelbrot, 1967). This work was based on the work of Lewis Richardson, and English mathematician. Richardson’s work on coastlines found that the length of a coastline was a function of the method used to measure it that is if we measure a coast with a 1mile ruler and then measure it again with a 1meter ruler we would find the measurement would grow significantly. Mandelbrot extended Richardson’s work and introduced the idea of fractal geometry and this self-similar complex property in his 1967 paper as well as beginning to discuss some of its applications to measuring natural processes. Within the paper, Mandelbrot demonstrated that the coastline of Britain couldn’t accurately be measured using traditional length measurements and instead needed an approach that embraced the complexities of the bays and cliffs that make it up.

To measure this roughness found so commonly in nature Mandelbrot needed a tool to quantify what he as saying, in his search he found the work of Felix

Hausdorff (1919). Hausdorff's work was considered something of a joke in the mathematics community, in its basic form, it stated that dimension doesn't always need to be an integer, and objects can lie between multiple dimensions. Mandelbrot believed that non-integer dimension could be a good measure of this roughness of nature. In traditional Euclidean geometry a line has a dimension of 1, a square has dimensions of 2 and a cube a dimension of 3; Mandelbrot used this idea to address the issues of shapes that were more than a square of 2 dimensions but failed to fill the 3 dimensional field of a cube. Hausdorff's (1919) work gave Mandelbrot the key and vocabulary to defining a fractal shape.

Re-visiting old mathematical problems interested Mandelbrot greatly, and in his youth he was inspired by his Uncle Szolem, who had told him by solving one of these pathological problem he would have a prosperous career in mathematics. The idea of shapes and objects that didn't fit into traditional Euclidean dimension (or 1, 2 or 3 dimensions) was an old concept, but these irregularities had been deemed pathological because the solution could not be reached using the Euclidean idea so strongly established in the mathematics community. These ideas fascinated Mandelbrot and can be traced as the foundation of fractal geometry.

Georg Cantor was the first to offer a problem that couldn't be answered using existing ideas about dimension. Cantor (1883) developed a set of rules to make a shape, now referred to as the Cantor Set (See Fig. 3.4). Within it he took a straight line and broke into thirds and then took away the middle section then continued this set of rules of each new line given from the previous step, logical thinking would assume that eventually there would be nothing left to throw away, but this wasn't the case, the pattern continued into infinity, each time you zoomed closer to the pattern, you were left with the look of the whole image. An exactly self-similar pattern could be seen at increasingly magnified scales.

Figure 3.4- Example of the Cantor Set

Helge von Koch also developed a shape with similar qualities. To develop a version of his name sake (see Fig 3.5), the Koch curve (1904) you take a triangle, and on each side split it into 3 and take the middle piece and substitute 2 pieces that are no longer than the original piece, and continue this pattern, every iteration adds a new triangle shape to the pattern, if you iterate this pattern an infinite amount of times you end up with a shapes that is infinitely long, it is a paradox to traditional mathematical measurements, a pathological curve. In both cases the image was infinitely complex but was confined within the 1 dimensional curve, it would never reach a 2 dimensional square but visually it was much more than a simple line.

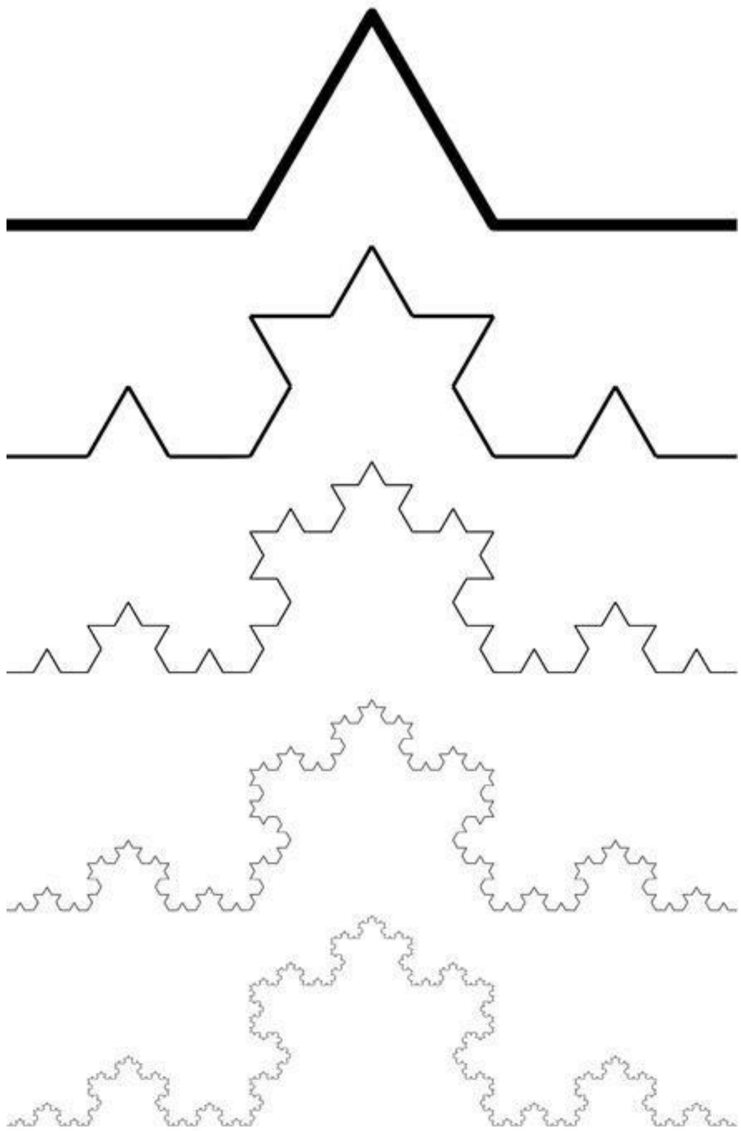

Figure 3.5- Example of Koch Curve

Mandelbrot's creativity left him enthusiastic to try to use new technology in the search for answers to his problem. During their early stages of his research, he used computers to work on yet another old mathematical theory. Gaston Julia’s work looked at feedback loops and iterations, he wanted to see what would happen if he put a number through an equation and used the results to again run the equation, and so on. This amount of iteration was time and effort consuming by hand, which meant that Julia was never been able to resolve his theory, however Mandelbrot with the ability of computers to do this sort of iterations, hundreds, thousands or millions of times was only a matter of pressing a few buttons.

Mandelbrot, as discussed before wanted to be able to put the visual world back into mathematics and he believed the 'pathological' mathematics problems of the 20th century perhaps held the key to understanding this roughness and complexity he was seeing in nature. Once he ran all Julia sets using new computer technology, the numbers he got he plotted the points on a graph. The images he began to see were complex and beautiful, they also had a familiarity about them. After running many examples of this, Mandelbrot eventually wrote a formula that plotted the results of all the Julia set's, this output was to form the now iconic face of fractal geometry, the Mandelbrot set (see Fig 3.6). This shape of infinite complexity represents the idea of fractal geometry; it is an epitome of the rules of fractal geometry. The self-similarity and scale invariance means it is the perfect example of fractal geometry, and its inability to be measured by Euclidean methods highlights its importance to the new field. Fractal geometry was born.

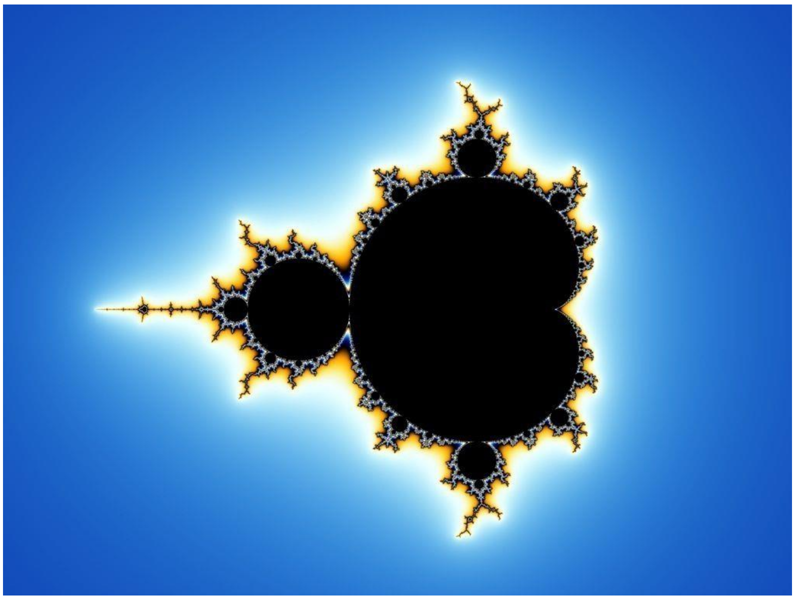

Figure 3.6- Mandelbrot Set

3.2.1 Defining a fractal shape:

Above tells the story of how Mandelbrot developed the concept of mathematical fractal geometry. We see its place in addressing many of the historical issues within mathematics and defining our visual environments, however the concept of fractals far extends its mathematic foundations. In more recent years, the concept of a fractal has become more difficult to define universally as these patterns are found in many places and processes however there are several characteristic qualities found in fractal patterns and processes. Mandelbrot (1983) defined fractals as a rough or fragmented shape that can be split into parts, each of which is, under differing magnifications, is a copy of the whole. Falconer (2003) extends this thought and highlights that among other features, a fractal has some form of self-similarity (including exact, approximate or statistical) and also demonstrates irregularity at some levels that cannot be described in traditional Euclidean geometric forms. These 2 features can be used to classify fractal patterns and processes.

Fractals can be found in a variety of different forms be it nature, mathematics, art or dynamic systems such as the weather or the human heartbeat. Generally, the field accepts 3 types of different fractal form; Computer Generated or mathematic which visualizes 'perfect' infinite fractal forms; Natural fractals which can be found in many natural patterns and processes and finally Artistic Fractals, which can incorporate both of the above forms of fractal, this type of fractal is man-made and developed with the purpose, among other things, to evoke aesthetic responses from viewers.

3.2.2 Different types of Fractal:

Without the development of computers, fractal patterns could not exist. In the development of the Mandelbrot set, many visual images were created. The most iconic image of fractal geometry, the Mandelbrot set, perhaps serves as the best example to computer generated fractals; this infinitely complex image has captured the imagination of the world. Since its development computer generated fractals have grown in use, the work laid the foundation for creating accurate and natural looking landscapes using these simple rules, which has changed the face of graphic design. Computer generated fractals are simply a visualisation of this short equation, but enables us to see visually what these means, allowing us, as Mandelbrot desired to put the eyes back into scientific research.

Natural fractals are those, which exist in the natural world, look outside now and you are likely to see a tree, a cloud or mountain scape (if you are lucky) something that demonstrates the scaling found within fractal geometry. Unlike mathematical or computer-generated fractals, natural fractals differ in the range of magnification. 'Perfect' fractals, such as the Mandelbrot Set can be magnified infinitely; each zoom will reveal a new but equally complex image. Natural fractals have a limited range; they can only be magnified up to a certain point. Despite this limitation in magnification and characteristic self-similarity, evidence has found that even in a small range, of just 25, is enough to account to aesthetic responses (Spehar et al., 2003). The list of naturally occurring fractals is endless, tree's, cloud's, waves in the sea, the branching of a river, the structure of a mountain, and the distribution of the stars in the sky, fractals patterns are even found within the human body, for example in the structure of the lungs with the branching bronchioles. The irregular patterns of a beating of the heart, research in fact found that a fractal heart beat is a healthy heart beat, and if the heart beat becomes too regulated and ordered this is a sign of ill health (Cipra, 2003).

3.2.3 Fractals in Art & Aesthetics:

The use of fractal patterns and acknowledgement of the self-similar irregular structures has been used by artists for many centuries. The link between fractal patterns and art was made by Mandelbrot when he referred to Hokusai's 'Great Wave off Kanagawa' he highlighted the self-similar structures used by the artist within the waves.

Figure 3.7- Great Wave off Kanagawa (c. 1829-32) Katsushika Hokusai

Fractal patterns have also been traced back to ancient times. Ron Eglash (1999) wrote about the presence of Fractals in many Rural African artistic products, as well as community structure. Could it be argued that a better understanding of nature held by societies within a rural setting and less time or exposure to Euclidean geometry found in urbanized societies?

The works of Richard Taylor (2010), a physicist and Artist have discovered the work of Jackson Pollock demonstrated fractal properties. His research found that despite its chaotic and messy appearance is actually underlying structure displays ordered and deliberate fractal patterns.

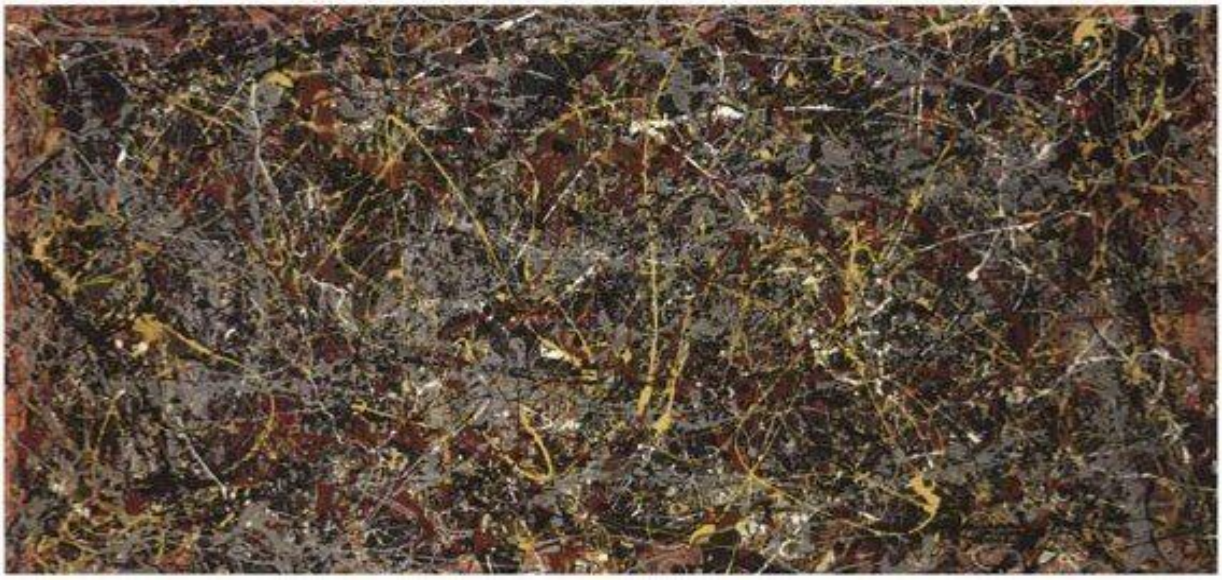

Figure 3.8- No.5 (1948) Jackson Pollock

The fascination with fractal geometry still remains of interest to modern artists- some such as Rhonda Roland Shearer have experimented with the next perspectives fractal geometry can have on sculpture. Her work such, *Geometric Proportion in Nature Study No. 1* (see fig. 13) combines both Fractal and Euclidean geometry to explore the interplay between the 2 in everyday life.

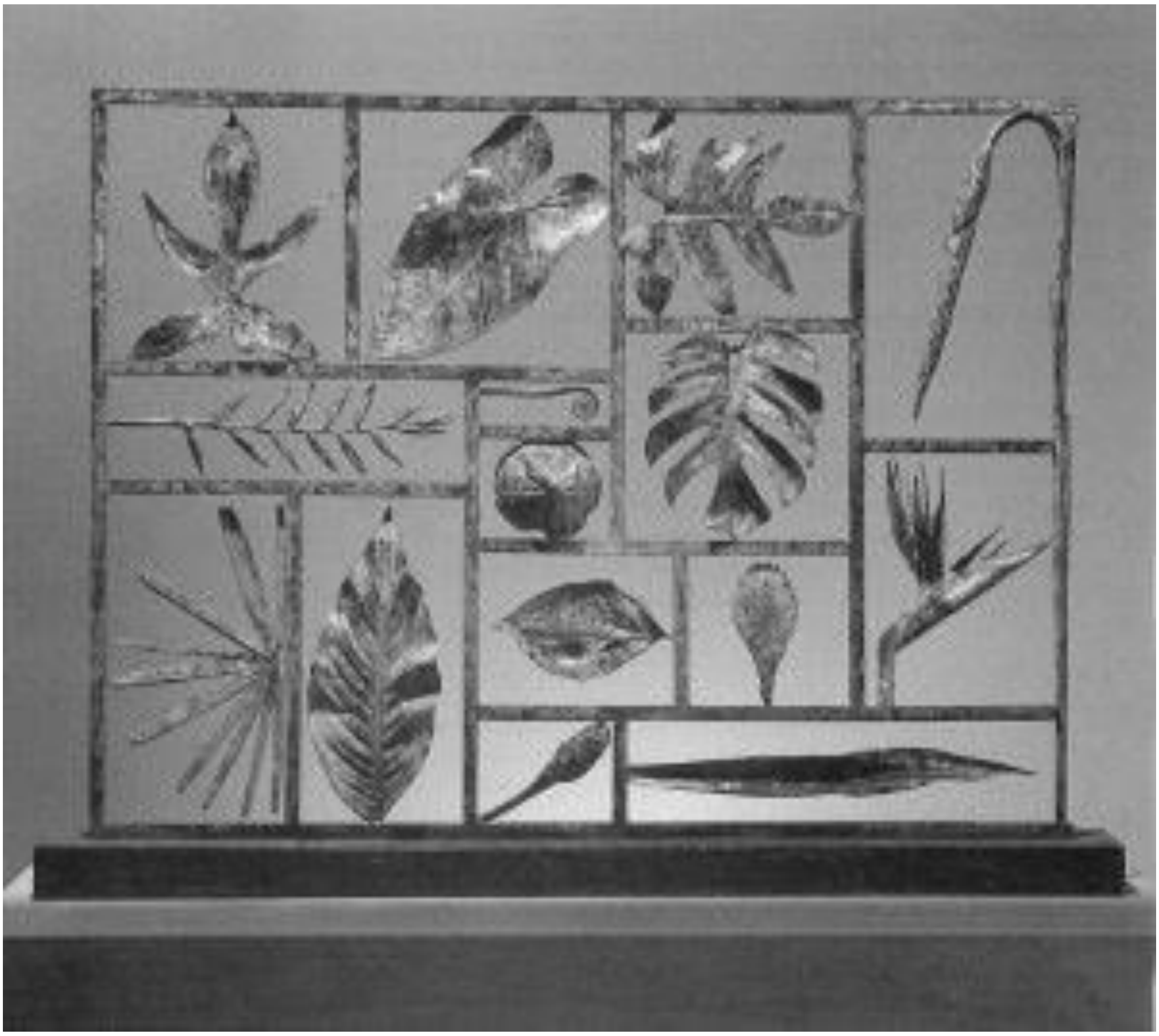

Figure 3.9-Geometric Proportions in Nature, Study No. 1. (1987) Rhonda Roland Shearer

Computer artists have also found inspiration in not just natural fractals but the mathematic computer generated patterns such as the Mandelbrot Set. The infinitely complex shapes are appealing and strangely hypnotic and can be found commonly on screen savers.

The use of fractals in Art from all ages makes the link to aesthetic response clear, there appears to be an aesthetic draw towards the complex shapes of nature, and as with many perceptual discoveries of the 20th century, it appears the Artists knew about them first. In more recent years, empirical studies exploring this aesthetic response have been conducted in an attempt to understand the appeal of natural patterns that Artists appear to have known for centuries.

3.2.4 Aesthetic Response to Fractals:

The links between beauty and nature are long established, with philosophers and artist's alike hunting for new ways to represent and mimic the processes of nature in their art. The links between fractal geometry and natural processes has been established since their discovery in the 70's by Benoit B. Mandelbrot, and since then artists and mathematicians alike have noted their beauty (Peitgen & Richter, 1986). Fractal geometry offered a much needed new way to quantify nature, as for many years the traditional Euclidean shapes did not come close to mirroring the complexity found within nature's patterns and processes. Since natural processes are linked to the development of fractal geometry this relationship is at its core, it seems only reasonable then, to investigate the role that fractal geometry plays in our experiences of beauty and aesthetic response as found also in aesthetics and nature.

It is note that fractals in their development have not always been considered beautiful. The history of fractal geometry dates further back than Mandelbrot and his elusive infinitely complex set to a time when these patterns were first developed and regarded as "pathological". Ironically these shapes where considered pathological because of their apparent disconnection with natures shapes, the academic world was dominated with Euclidean geometry as an explanation for tress, mountains and coastlines, leaving little room for these radical ideas of scaling and iteration that were in fact in abundance in environment, but were so difficult to see without the right language to describe them. This opinion was of the majority until Mandelbrot offered an alternative view, perhaps *"clouds are not spheres and mountains aren't cones"* and in fact to consider them so would be to take away the beautiful complexity, and reduce them to less than their parts, a view aligned with Gestalt theorist of perception.

Mandelbrot's first glimpse at the Mandelbrot Set was, he said filled with a sense of familiarity, that the shapes that could not be viewed without the dawn on computational process was something he felt he had seen many times (Lesmoir-Gordon, 2010). He was quick to acknowledge the aesthetic power of fractals and extended this thought to say that fractal shapes mimicry of nature was the key to the aesthetic appeal (Mandelbrot, 1982).

Although seemingly from the start the links was established between fractal geometry and aesthetic appeal, it was not until the 90's that the empirical investigation of appeal and fractal images began. The first piece of research collected data on aesthetic appeal of fractal images found a preference towards images that had been generated by chaos opposed the then non-chaotic counterparts (Taylor, 1998). These results showing not only a preference towards fractal patterns, but also demonstrating our perceptual ability to distinguish between the two- asking the question is this an innate skill held by us all? And if so, what could its purpose be?

As research into the field developed, a pattern of preference began to emerge from the data. This pattern highlighted an optimal range of fractal preference; while research has already established the aesthetic appeal of images displaying fractal properties (Taylor, 1998) an optimal range began to emerge from the fractal spectrum that seemed to demonstrate higher universal preference. Differences between natural fractals, computer generated fractals and artistic fractal images, despite the links between all three types of fractal each type appears unique and can be easily distinguished with the eye. From the three, natural images are universally preferred, however all categories if viewed separately demonstrate a preference for mid-range FD scores (Spehar et al, 2003).

In early research there seemed to be inconsistent results between the optimal aesthetic range, early research used varied forms of stimuli including computer generated and photographic representations of natural stimuli and this mismatch in experimental design has been held responsible for the conflicting results. Pickover (1995) reported a D value of 1.8 as the most preferred, in the study, which used computer-generated patterns. These results are conflicting with Aks & Sprott (1996) study that also used computer-generated fractal patterns but found a significantly lower optimal aesthetic D value of 1.3. This variance in results, lead to the opinion that no optimal preference range exists (Taylor et al., 2001) and instead preference was dependent of how the images were generated, whether they be natural fractals, computer generated fractals or artistic generated fractals, such as the abstract work of Jackson Pollock.

After investigation Taylor et al (2001) failed to validate this hypothesis and found instead that mid-range D values (1.3-1.5) were consistently preferred regardless of how the fractal images were generated. (Taylor et al., 2001, Spehar et al 2003) and this finding is the prevailing view within the modern field.

Given that the preference falls between a range of D values rather than on a specific D value, theories have been put forward to account for the individual differences between preferences. Personality factors have been suggested to contribute to the differences in preference, with preference for higher D values in creative people (Richard, 2001), this result was tested further by Aks & Sprott (1996) who found that participants who deemed themselves to be creative on self-report measures, contrary to previous research, found that they had a preference for slightly lowered D values, this could be suggested as an indication that other factors and not personality may influence the level of preference in D values. Hagerhall et al's (2004) results suggest that preference peaks at D1.3 and after this point begins to drop, however the study failed to used a full range stimuli sample, therefore we cannot infer that with these higher D images the results would have given the same results. This peak in mid-range fractal demonstrates links between perceived complexity and fractal dimension, as discussed previously in Berlyne's (1971) hypothesis. Demonstrating the suggested link between visual complexity and fractal dimension. The 2 constructs appear aligned, however research into their comparison is currently lacking.

The correspondence between mid-range fractals and nature could be suggested to explain why we preference D values between 1.3-1.5, Aks & Sprott (1996) suggest that people's preference is universally set at 1.3 because of continual visual exposure to nature's patterns, however more recent evidence would suggest that there is significant variation in the D values found in nature. Clouds do indeed exhibit 1.3 D values (Lovejoy, 1982) as do waves (Werner, 1999) however coastlines have much more variety with evidence suggesting a range between

1.05-1.52 (Mandelbrot, 1982; Feder, 1988) and the distribution of stars in the scale demonstrate much lower D values (Mandelbrot, 1982)

As demonstrated above, further research in needed to fully understand the meaning of the strong draw towards mid-range fractal preference, This author believes it is important to understand why the evidence seems to point towards a range of preference instead of a exact value, what other factors influence our aesthetic opinions? It has been suggested that *"fractal dimension could provide part of the explanation to the well-documented connection between preference and naturalness"* (Hagerhall et al., 2004) and this link could make the argument that fractal measurement could be used as an indicator of the 'naturalness' of an image given the established links between nature and fractal patterns.

If fractal identification is indeed inbuilt into our perceptual and cognitive systems, we need to ask the question, why is this so? The ability to distinguish between fractal images is highest if the images used correspond to D values found in nature (Knill, Field & Kersten, 1990) Superior ability to distinguish between different D values has been suggested by Geake & Landini (1997) to demonstrate excelling in 'simultaneous synthesis'. This ability to distinguish between D values is intrinsically linked to the visual system, which has been suggested throughout the research to be a factor in our association with fractal images. The perception involved in viewing fractal images is, it seems, an innate human function.

Evolutionary perspectives have been offered as an explanation for the preference of fractal patterns, Rogowitz & Voss (1990) suggest that for millions of years, humans have been exposed to nature's fractals and during this time our visual system has evolved to recognise them with ease. The environment we spend the most time in today is significantly different to the natural world in which we evolved, the world is filled with Euclidean shapes in buildings, roads and computer screen and even if we can see nature, it seems consistently to be viewed through these Euclidean confines. This theory demonstrates wider links to the theory is aesthetics, and the questions of why are we drawn to beauty? Evolutionary theory suggest we are drawn to certain images or scenes because they are related to our survival instinct (Ulrich, 1993, Wise & Leigh-Hazzard, 2000) and this will be explored more thoroughly in the next chapter.

Evolutionary theory offers another level of preference on the fractal D spectrum. Wise & Leigh Hazzrd (2000) found that observers demonstrate preference at a lower D value because these scenes mimic the properties of African Savannah scenery, were our ancestors spent a large part of their evolutionary history. Fractal patterns that evoke positive aesthetic responses have been termed “biophilic fractals” this link is connected with the natural forms that are deeply rooted in fractal patterns (Taylor & Sprott, 2008).

The study of fractals only adds another degree to the growing topic of the nature/nurture debate between aesthetic preferences. Do we find images beautiful because we are programmed to, we have inbuilt senses to view environments as appealing or not so, Or do our aesthetic judgments depend largely on our nurture and the environment in which we have grown, in this case cultural differences would be evident in aesthetic judgment. This prevailing question is one that this thesis attempts to explore, adding much needed new research to the field of fractal aesthetics, to address the questions and gaps within the current literature.

Conclusions:

It could be proposed that fractal dimension is a factor in a larger multidimensional construct of visual complexity. The labels ‘rough’, ‘chaotic’ and ‘messy’ all have parallels within the field of visual complexity measures. Whilst evidence has shown that fractal dimension is a distinct factor from visual complexity as we currently define it (Forsythe et al, 2010) the similarities between descriptions and aesthetic responses patterns warrant a deeper exploration than currently provided. This thesis will explore these links.

The evidence pointing towards a universal preference for mid-range fractals is based on a small group of studies that cannot demonstrate the wider demographic differences between distinct samples and despite their strong and intriguing findings. This thesis suggests the field have been premature to make assumptions about universality before a systematic exploration of factors that contribute to aesthetic preference for fractal patterns is fully explored. Here we attempt to fully clarify the current gaps within the field to make judgments regarding the links of fractal geometry and visual complexity and the role that both these, possibly intertwined concepts as well as individual experiences play in aesthetic judgments.

4.0 Cross-cultural, sub-cultural and further factors influence on Aesthetic Preference:

The following section explores the current literature into Cross and Sub-Cultural factors that influence aesthetic response to a variety of stimulus. It will explore cultural and sub-cultural factors using a range of literature from different disciplines. This chapter examines responses from Empirical Aesthetics, Art and Nature because each of these areas (particularly nature) has been found to contain fractal patterns. The majority of findings suggest that there does appear to be consistencies in visual preference across cultures, particularly when looking at aesthetic responses to landscape. This offers support for existing theories in Empirical Aesthetics towards universal patterns of preference. Further to this however, is the evidence suggesting that sub-cultural factors and most powerfully, experience, play a role in some cases, towards shaping our preferences. These findings raise questions about the 'universality' of mid-range preference (Spehar et al., 2003) conclusions raised in fractal aesthetics research, considering the evidence is limited and still relatively unexplored. Most of the literature reviewed within this section is dated, and inferences can only be made to fractal patterns cautiously. However on the whole, the current literature demonstrates the requirement for further evidence exploring how cultural and cross-cultural factors can influence preference for fractal patterns.

Much of the historical research in empirical aesthetics aimed to find universals in judgments and preferences. Some researchers however explored the differences across cultures and countries, the impact of sub-cultural divide and visual environmental differences, including rural and urban populations. The following section looks at a variety of studies from different disciplines including empirical aesthetics, art studies and landscape design exploring general opinion as to whether preferences are shaped by our cultural background or are founded in universals based on innate biological drives. The stimulus explored includes art, abstract geometric shapes and nature. Limited research has been carried on cross-cultural differences in preference for fractal patterns and this section uses a variety of sources from which understanding of our responses to complex, aesthetic and natural images (all with fractal foundations) are shaped by our cultural experiences.

4.1 Cross-cultural Difference in Aesthetic Preference Literature:

The anthropologist Robert Lowie (1921) laid the groundwork for exploration of aesthetic responses across cultures to explore if universals or individual differences underlie our influence aesthetic preferences. He hoped that his brief inquiry would stimulate and inspire further and more thorough investigations. His study explored the decorative artistic and abstract style of Crow parfleches and compared these to the perfleches of the Shoshoni tribe. A Parfleche is a 'folded rawhide carryings bag made by the plains Indians of North America', which is decorated with colour, basic geometric abstract design (Britannica encyclopaedia, 2014). His results found that there were observable and measurable differences between the abstract patterns of each group's parfleches design. Interestingly, in comparing the proportions of the geometric shapes, to that of the 'golden section' proportion (Fechner, 1860), Lowie found neither group demonstrated the measurement as a the universally preferred proportion, rather the Shoshoni norm fell above Fechner's proposals, and Crow ratios fell below.

As Lowie (1921) had hoped, the exploration of cross-cultural differences in preferences continued to grow into the 1950's with findings demonstrating high correlations in aesthetic responses between Australian Aboriginals and Caucasian participants (McElroy, 1952). However, authors began to raise concerns over the existence of universal aesthetic principles arguing that beauty could more reasonability be determined by culture. Researchers, including Lawlor (1955), began to credit cultural experience as an overpowering component in understanding aesthetic universals that may exist when looking between two or more very different cultural heritages.

Larger scale cross-cultural differences in visual perceptions were explored using geometric illusions. Some included samples from up to 15 societies over a period of 6 years (Segall et al., 1966). It was hypothesised ahead of Seagall et al's study that people from different cultures would be differentially susceptible to geometric illusions because they have discovered different visual habits that may produce/inhibit particular illusionary responses. The result confirmed this hypothesis; generally western samples were more susceptible to the Muller-Lyer and Sander parallelogram illusions, than non-western counterparts. These and other differences found in susceptibility to illusions were believed to be a response to cultural and ecological factors in the visual environments from which the different participants were sourced. This again raised the question regarding the strength that macro-cultural factors (country) have, against the strength of micro-cultural factors (participants immediate visual environment).

Such differences between visual illusion susceptibility are not grounded in biological racial difference; rather they appeared to be a result of differences in experience and susceptibility to visual illusions (Segall et al., 1966). These findings support the theory that our perceptions are acquired through experience. This understanding is important to the current thesis as we attempt to explore how visual experiences across culture, countries and sub-groups may influence our perception and in turn preference of fractal patterns.

Research continued looking at cultural differences in landscape preference, in one study a comparison between native Arctic and non-native Arctic workers, and those with no Artic experience as participants (Sonnenfeld, 1967) suggested that that landscape preference was a result of different cultures (native/non-native

Artic residents), and within these cultures, preference was influenced by factors such as meaningfulness and similarities to native landscape. These results lend support to arguments that experience increased preference such as the role that mere exposure (Zajonc, 1968) or meaningfulness (Martindale et al, 1988) play in shaping visual preferences.

The power of cultural ties in aesthetic values was further researched by Iwao & Child (1966), an as they examined evidence to support the notion that universal truths of aesthetic evaluation in art exist across cultures. Art experts (potters) were recruited from Japan and findings were to be compared to previously collected rating data for equivalent participants from the United States. Participants were recruited from a number of villages and from a number of different pottery families. A two alternate forced choice design was used with colour and black and white art images and participants were asked which, in their opinion, was the better piece of art, translated into Japanese. Iwao & Child (1966) report consistency in aesthetic judgments between both cultures, suggesting that those with an interest in art demonstrate agreement in aesthetic evaluation despite their own cultural heritage, however on closer interpretation individual differences are evident in the sample. The authors suggest scenarios including the possibility that Japanese participants may have been exposed to western art or may have influence their results to match the US counterparts. However further analysis of students within the local area reveal lower similarity scores than those seen between the 2 groups suggesting some universality between art interested individuals exists regardless of tradition or experience within culture. Child and colleagues went on to run supplementary studies looking at cross-cultural differences in aesthetic response and found, as a whole, evidence that points towards universal aesthetic exceeding the bounds of ‘culture’ as we classify it (Child & Siroto, 1965; Ford, Prothro & Child, 1966; Child & Iwao, 1968; Iwao, Child & Garcia, 1969).

Similarity Soueif and Eysenck (1971) and Eysenck & Soueif (1972) recruited British and Egyptian art students and lay people (non-art trained participants) to explore aesthetic responses. Participants were asked to rate Birkhoff’s (1933) polygons for pleasantness. Results showed interesting differences between cultural responses to these shapes. British art students showed preference for simple figures, and British lay people preferred complex figures. This trend is reversed within the Egyptian sample with art-educated participants preferring the complex figures and the lay participants demonstrated preference towards the simple images. Despite this curious directional result, no significant differences where found between the British and Egyptian groups as a whole. There were also no significant differences in preference between both art and non-art trained participants, although the trend seemed to suggest reversed trends for complexity preference, but these differences were not significant. Eysenck and Soueif (1971) did not believe that their data support considerably large differences in aesthetic preference between both cultures but instead hint towards more universal preferences over cultural issues.

In a further experiment, Soueif and Eysenck (1972) studied if the factorial structure of the scores awarded by Egyptian participants to Birkhoff's (1933) polygons was comparable to the one revealed by a previous study involving only British participants (Eysenck & Castle, 1970). Results unpicked further the factors underlying the aesthetic preference of British participants and how these differed to their Egyptian counterparts. The authors concluded that, whilst there was a predisposition between cultures to prefer certain polygonal figures, such as heightened preference in the UK sample for the cross because of the semantic associated which may be strong to the UK a more proportionally Christian society than the Egyptian sample. These findings, the author believes, proposes the possibility of a more deeply based, biologically determined cause for aesthetic judgments, rather than preferences being a function of cultural or environmental experiences (Soueif & Eysenck, 1972.)

Eysenck & Iwawaki (1971) used a similar design to explore aesthetic responses of Japanese and British Participants. The results again demonstrated no significant differences between the cultures sampled. There were high correlations between the two groups, however analysis revealed that British participants generally rated pictures more highly than their Japanese counterparts. The findings suggest similar trends as seen in previous studies that there may be underlying universal preferences for geometric shapes. Despite the results between cultures demonstrating no significant differences, large individual differences between participants were reported. These findings suggest that perhaps other factors (stronger than cultural bounds) can influence visual preferences for abstract or geometric shapes.

Researchers within the field of empirical aesthetics continued to investigate cross-cultural differences in polygon complexity. In one such study, aesthetics judgments for polygon shapes (varying in complexity) were collected from 5 different cultures including the United States, Korea, China, India and Turkey (Farley & Ahn, 1973). Results were in an agreement with the existence of an aesthetic universal for complexity, which appears to have a similar influence across the different cultures adding credence to the previous results emerging from other academics working in the same field. The finding of this study however should be noted with caution as although the cultural-origin of participants was across the 5 different cultures outlined, all participants were recruited while studying in the United States. This factor means that the visual experiences of participants would have been similar at the time of testing, meaning that the potential influence of learned preferences for (micro) environmental features should be considered during interpretation the results.

The role of sub-cultural or micro rather than macro cross-cultural environmental impact of preference is a further factor to considered when exploring the impact of culture in aesthetic responses. Studies have found great variability within sub-cultures in societies compared to relatively smaller variables across-cultures and society when looking at participants from Australia, Pakistan and Thailand (Anderson, 1976). The results show general consistency between preferences, but marked significant differences based on sub-cultural groups such as demographic details and background. For example within the Australian sample, preferences of participants from a suburban environment and school differed significantly from participants from an urban and industrialised environment and school. In additional to contributing to the knowledge of cross-cultural aesthetics Anderson (1976) highlighted the experimental/methodological issued faced by researchers at the time, which cause difficulties when collecting cross-cultural data. The author discusses the differing methods in obtaining aesthetic judgments. This acknowledgement sheds light on the previous challenges faced, and highlight the necessity to take conclusions of these and related findings cautiously.

Previous findings emphasise strong agreement for landscape preference from participants from generally similar cultural background. These studies focused mainly on scenic qualities of landscape rather than consideration of heritage qualities (and sense of connection) with landscape. Zube & Pitt (1981) wanted to explore the gaps in literature. Their study considered Yugoslavian, West Indian and American participants response to different landscapes, both scenic and of cultural heritage to each group. Results stress the importance of individual differences as a contributor in preference formation. Significant differences between cultures were reported, however there are equal if not greater individual differences within cultural groups that influence our landscape preferences and scenic judgments. One such difference involves the presence of only nature or man-made structures in the scenes. Previous findings show general consensus that natural scenes are preferred other those displaying man-made structure (Fines, 1968; Kaplan et al., 1972) however Zube & Pitt's (1981) findings show that not all cultures share this perception that scenes and landscapes including man-made structures are necessarily less appealing or scenic than those of only nature. These findings were supported in later exploration demonstrating high agreement for scenic preference and judgment when cultures are relatively similar (Zube, 1984). While large breaks in research into cross-cultural difference exist, McManus & Wu (2013) demonstrate the continued presence of cultural considerations in modern empirical aesthetics. McManus and colleagues (2010, 2013) found support for universals in rectangle preference across cultures but noted the smaller scale individual differences between preferences.

Summarising the literature above, results appear to show mixed findings. While there is evidence to suggest that universal and perhaps biological basis for preferences for landscape, art and patterns can be seen across a wide variety of cultures, and in relation to the current thesis, these findings would support the current theories of universal fractal preference being based in evolutionary and biological foundations. Despite these conclusions, many studies above comment on the role of sub-cultural or individual factors in forming preference. It can be argued that the environments in which people spend time can vary vastly across culture/countries. The results above suggest that it may be a fruitful area of investigation to examine the sub-cultural and individual differences between aesthetic judgments.

4.2 Sub-cultural factors:

A summary of these findings would suggest little variation across culture in preferences for controlled shapes. In landscape or art however we can see the power that sub-cultural factors appear to have over our preferences. These factors seem more dominant than the general classification of 'culture' or country alone. More specific visual experiences other than the country or culture in which we live and develop, have been considered as contributing factors to aesthetic responses towards art, nature and visual experiences. More specifically, the following literature will explore the differences in aesthetic response based on urban and rural environmental experience as well as the impact that sub-cultures such as education background and expertise can have on our visual preferences.

This thesis asks if the exposure to the environment, whether it be full of Euclidean geometry and commonly seen in urban environments or fractal geometry in rural environments could influence our visual preferences for such visual patterns. Kelly (1955) believes a person uses there past experience to interpret current visual experience, therefore our exposure to specific environments or visual scenes may influence our aesthetic judgments. Brunswik (1956) supported Kelly's notion, theorising that relationships between landscape and personal outcome is acquired through experience. To support this case, links can also be made to 'place identity' theory (Canter 1973, Proshansky et al., 1983), which places importance of past experience on evaluations of environmental quality.

Empirical support for this position has found differences in preference for natural settings. Differences in preference between inner-city school children and environmental educators have been reported (Medina, 1983), with marked urban/rural differences in preferences and heightened preference across groups for the scenes they experience more regularly. Again this evidence supports the mere-exposure hypothesis (Zajonc, 1968) and the processing fluency hypothesis (Reber et al., 2004). Rather than the general classification of the wider macro cultural environments, the micro-environments individuals spend time in are influential in shaping preference (Medina, 1983).

Contrasting results have been found when exploring responses only to urban over rural scenes. Nasar (1984) conducted a study in which participants from Japan and the United States were shown pictures of urban street scenes and results demonstrate that, in contrast to Medina's (1983) findings, each group preferred the non-native rather than the native scenes. The author concluded that instead of familiarity effect for preference in native environments, the factors of 'order' and 'diversity' were the main predictors of preference for urban street scenes. Results also suggest that other individual factors such as 'prominence of nature' were potential predictors of preference. These findings demonstrate the inconsistency in reported results between urban and rural environments on landscape preference (Nasar, 1984). It should be said however, that such findings might be limited as the sample population only included urban scenes and failed to measure if differences were consistent in rural scenic landscapes.

Further studies provided a wider insight into individual factors that contribute to aesthetic judgments of landscapes. Dearden (1984) explored the impact of training (examining those in the landscape planning profession and those who were not), impact of environmental awareness, and differences in familiarity to the general landscape used. Dearden included participants from various socioeconomic factors and findings suggest no bias in preference for landscape based on professional training, unlike previous studies of preference (including Souief & Eysenck, 1971). Dearden did however find highly significant differences between groups, which have experience evaluating wilderness scenes and those who did not. Familiarity with the landscape appeared to be positively correlated with landscape preference. For example participants expressed more positive feelings toward natural scenes if they had previous experience within these environments rather than those living in high-density housing environments. Further demographic details such as gender, age, annual income, and education or occupation background did not demonstrate significant relationships with landscape preferences. These findings suggest that sub-cultural environments, such as the differences in landscape preference between those living in urban and industrialised environments and those living in rural or environments containing more natural features.

During the 10 years following these studies, Yu (1995) again explored sub-group differences in landscape preference in a Chinese sample of student landscape architects and horticulturist's. Students were from both urban and rural environments, and cross-cultural comparison included a design expert group from the US. Results supported Dearden's (1984) and other conclusions (Zube & Pitt, 1981; Schroeder, 1983; Kaplan & Talbot, 1987), that the environment in which participants lived (Urban vs Rural) was a powerful predictor of the variance in preference for landscapes. Some weak cross-cultural differences, between macro-culture (such as across countries) were found, however Yu (1995) concluded that preferences could be overridden by living environment or education experience.

There is limited research looking at aesthetic responses to a variety of stimulus (other than pure landscape studies between urban and rural population). The history of empirical aesthetics suggests that visual experiences change our aesthetic response to these stimulus (Reber et al, 2004; Zajonc, 1968) therefore this thesis aims to highlight this gap within the literature and will attempt to explore this factor from a more stringent experimental angle. The current thesis aims to expand this area by exploring the impact of environmental background on preference for fractal dimension as the presence (or absence) of fractal patterns in visual environments in an attempt to begin to fill this currently unexplored avenue.

Experience with natural environments appears to influence not only preferences as explored above, but also have an impact on behaviour and moral judgments. Several studies have demonstrated the links between experiences with nature and behaviour in later life in terms of conservation. Wells & Lekies (2006) explored the links between childhood nature experience and views and behaviour towards environmentalism in adulthood. The study looked a these experiences in a large sample of 2,000 adults and found that childhood experiences in natural environments, particularly for 'wild' nature had positive results on environmental attitude in adulthood. Additionally those with wild nature experiences were associated positively with environmental behaviours whilst those with only domesticated nature activities (such as gardening interest) did not have as strong an association with positive environmental behaviour.

In a later study, Zaradic, Perhams & Kareiva (2009) found similar results. Time spent hiking or backpacking in wild nature had positive correlations with monetary contributions to conservation up to 11-12 years after these experiences. This relationship is negative with those who spent time in public or domesticated land or in activities such as fishing. These results appear to show a worrying trend in decreasing experience with wild nature resulting in much less environmental identification in years to come. These results demonstrate links between sub-cultural groups that partake in nature experiences over those, most likely urban populations, who do not have these similar experiences that not only appear to have less aesthetic response as well as less behavioural response.

Whilst sub-cultural distinctions can be made between rural and urban environment, this classification is open to other interpretations and one such example could be the differences between personal interests or education and background as a further sub-cultural distinction. An individual's personal interests, education history or employment experiences may effect how much time and attention is directed towards particular visual stimulus, studies have found very low correlations for preference between groups from different professional backgrounds (Buhyoff et al., 1978) and differences in preference between special interest conservation groups and university students (Daniel & Boster, 1976). Further findings have demonstrated that factors including knowledge and familiarity of a subject or landscape can affect assessment ratings awarded by individuals;(Kaplan, 1973; Gallagher, 1977; Anerson, 1978; Buyhoff et al., 1979; Hammitt, 1979) these findings offer support for existing theories of general aesthetic response that mere exposure (Zajonc, 1968) and ease in processing visual information (Reber et al, 2004) can have significant interactions with preferences ratings or choices.

This awareness of different preferences in sub-cultures is of interest in a variety of discipline including psychology, artists and different groups of designers. Buhyoff et al (1978) for example, reported landscape architects could accurately predict the preferences of 'client groups' based on verbal descriptions of them. It has been suggested that designers, and artists alike, have long since been aware of the subtle rules and differences between sub-cultures and how these play an important role in aesthetic responses. Mirroring Zeki's (1999) sentiments, the science appears to lag behind the artists in understanding the truths behind aesthetic judgments and responses from a variety of different groups.

This thesis summarises the literature in alignment with conclusions made by Kaplan & Herbert (1987) that preference are to some extent cross-cultural, but to a greater extent sub-cultural. The literature suggested that much more powerful predictors of preference, when looking at landscape in particular, lie within sub-cultura individual identity and experience. As evidenced above, visual experience such as urban and rural differences can have a profound impact on our visual experiences, whether this is an issue of self-identity and affective responses or a lower level by product of repeated exposure to a scene. The evidence as with cross-cultural studies is non-existent when exploring the sub-cultural difference in preferences for fractal patterns given it is a relatively unexplored field, however we can begin to make assertions regarding the possible presence of sub-cultural differences based on the literature reviewed above. It could be argued that if we are exposed to simple and largely Euclidean geometric shapes we develop preference for these over more complex natural shapes displaying, among other things fractal properties. The current thesis aims to explore this in further detail looking at how specifically low-level recognition (such as mere exposure) can account for or predict our preferences along the fractal continuum of complexity.

4.3 Further individual differences:

In addition to cultural and sub-cultural factors, other individual differences have also been found to account for variance in aesthetic judgments. Some of the notable areas of investigation include Age and Gender. Findings are varied when exploring individual differences and it may be because of the variety of stimulus used to measure the responses. In the light of very limited literature regarding aesthetic responses to fractal patterns, the following section will use evidence from a variety of different disciplines including psychology, art and landscape studies to make tentative links for potential impact of age and gender on aesthetic responses to fractal shapes.

Life Span:

As we age do our aesthetic responses change? This question asks the impact that ageing (both normally and abnormally) can have on our visual preferences. We have seen above, that our life experiences appear to influence our aesthetic judgments for landscapes, art and shapes but do human developmental stages such as childhood, adolescence and older age influence our aesthetic judgments? In addition to normal developmental stages in human ageing, we also need to consider the influence of abnormal ageing or development in later life such as neurological degeneration. Several studies have found interesting results when looking at the impact of dementia on aesthetic responses. Below summarises the current findings of aesthetic response across lifespan.

Within empirical aesthetics, researchers have explored the impact of chronological age on preference for rectangle of different proportion in a bid to contribute to Fechner's (1860) work on rectangle proportion. Thompson (1946) explored if children demonstrated preferences consistent with a rectangle of certain proportions, and if differences did exist, hoped to explore the point at which preference fell in line with adult preferences.

Thompson (1946) used 4 different groups, pre-school, 2 school-aged children groups and college student groups, each with 100 participants. Results found that college aged student's demonstrated similar preference to results collected from previous adult samples. The pre-school group showed no stable preference across all rectangles with very high individual differences across the sample. The younger school group (third grade in American schooling) demonstrated stable preference for rectangles of greater width, however these preferences do not correspond to the college student group. The older school aged children (sixth grade in American schooling) showed stable preferences, which were more consistent with the college-aged students than the younger school aged children. The findings suggest that as chronological age increases, children preferences become more and more similar to stable adult preference responses. In addition to the purely aesthetic exploration, Thompson (1946) believed that by exploring children preferences for simple forms this offered an excellent method of studying non-verbal transmission of culture within child development. Tracking when preference aligned with the group or adult 'norms' allowed assumptions to be made about when children learned to recognise visual cultural rules. Thompson (1946) concluded that during childhood, children learn to like proportion with which they are familiar and this demonstrates the role social and environmental experience has on developing visual preferences.

Within other studies it has been suggested that older children have a preference for abstract art, whereas younger children prefer images of objects, which are familiar to them (Rump & Southgate, 1967). However, such studies failed to control for the role of experience in aesthetic responses leading to arguments that age cannot be a strong predictor of aesthetic judgments (Taunton, 1982). A child's sensitivity to art and their subsequent responses will influence what they like and dislike however Taunton (1982) cautions against the use of comparison between children and trained/untrained adults in aesthetic research, suggesting that such comparison plays down the strong individual differences and idiosyncratic influence of preference developing with experience and learning outside of chronological age.

Aesthetic responses to natural environments have been found to show marked age differences. Findings are evidenced from a large sample of participants from a wide age range rated photographs of natural scenes (Balling & Falk, 1982). The study used two measures of preference, firstly asking how much participants would like to live at each depicted scene and secondly how much they would like to visit each depicted scene. Results demonstrated that children showed preferences for Savanna scenes over more familiar environments. Striking differences were seen in the adolescent sample, as this group demonstrated consistently lower preferences for all scenes compared to any of the other groups in the sample. It was suggested that perhaps the negative scoring was distinctive across all ratings, however within these low scores with the adolescent group included marked differences in preferences between the scenes compared with the other group preference patterns (Balling & Falk, 1982). Distinct differences between low ratings have been found within a secondary school sample (aged 13-17yrs) but not within a primary school sample (aged 10-12yrs) suggested that when assessing landscape or natural scenes, adolescent preference appears to be distinctively lower when compared to younger or older generations (Herzog, Herbet, Kaplan & Crooks, 2000).

Other studies have also demonstrated differences in preference of adolescents compared to younger and older groups for natural settings. Adolescents show a higher appreciation of developed and urban setting than their different aged counter parts (Kaplan & Kaplan, 2002). This preference does not suggest adolescents do not show appreciation for natural settings, however this preference is less marked than in adults or younger children. The authors suggest this pattern of preference is seen because of urban spaces being active and facilitating group and social spaces, rather than solo and natural scenes (Kaplan & Kaplan, 2002).

Similar patterns of adolescent differences were seen when exploring aesthetic responses to urban scenes (Medina, 1983). Whilst least preferred scenes were fairly consistent between the adult and youth samples, the younger sample showed the highest preference for scenes similar to that which is familiar to them. It is suggested that the younger adolescent sample preferred scenes depicting activity and mobility options where as the older sample shown highest preference for the quiet and private scenes depicting nature or natural elements (Medina, 1983).

Lyons (1983) conducted a study exploring demographic correlates of landscape preference, which included amongst other variables an exploration of the impact of age of ratings for vegetation biomes. Results found significant differences of ratings across the lifespan development with highest scores given by young children, significant divergence in adolescences and then the lowest scores given by elderly participants. Ratings showed divergence between urban and rural residents adding support to the sub-cultural findings discussed above. The study concludes that preferences do not appear to be based on age or other evolutionary theories but instead are formed in a complex process which involves experience and differential social factors at chronological points of lifespan development.

Elderly samples have been found to display relatively low preference for wild nature over more managed and developed natural landscape (Balling & Falk, 1982; Lyons, 1983; Strumse, 1996 and Van den Berg et al, 1998). Some have attributed this difference in elderly samples as relating to evolutionary drives that would make wilderness scenes a larger risk to vulnerability, both physical and psychological, Alternative theories such as increased cultural and experiential shaping have been attributed to this change in preference at older ages (Van den Berg & Koole, 2006) however studies in non-normal development appear to show stability in preference for art stimulus despite neurodegenerative diseases such as Alzheimer's, which suggests that in older age preferences remain stable despite the functioning capacity of working memory (Halpern et al., 2008). Other studies exploring neurological conditions however appear to show aesthetic changing in abnormal ageing, for example some individuals have been found to showed marked aesthetic differences in production following a stroke (Zaimov, Kitov & Kolev, 1969).

We can see from the literature reviewed above that preferences do appear to be bound with age, however the impact of chronological age alone is difficult to interpret as a separate influential factor in aesthetic judgments. Further individual experience, education and social factors cannot be uncoupled from age and as previous literature demonstrates these factors can influence our aesthetic responses to a variety of stimulus. There does appear to be marked differences in adolescents and in older adulthood for landscapes and it has been argued that perhaps social factors and priorities can account for this difference. Age alone cannot account for individual differences in aesthetic responses, but as the literature above demonstrates it is important to explore age as a factor amongst other individual differences when investigating this area.

The area of lifespan assessment of aesthetic preference and the literature discussed above however faces several interpretative problems, which should be noted. First and foremost, ageing is a complex progress that following no set trajectory, individual age individually and therefore the concept of chronological age is difficult to classify by certain standards or behaviours. A further interpretative issues arises for the ‘elderly’ or older populations sampled in the literature above, as we age our visual system and processing become deficient, particularly when the complexity of the scene being assessed is high as in the literature discussed above (Faubert, 2002). Perceptual abilities diminish with age, and it is difficult particularly using the designs adopted in the literature above to ascertain the individual perceptual ability of the participants taking part as well as the impact this may have on aesthetic responses. A further interpretative issues when assessing aesthetic responses across lifespan refers to the issues of non-normal ageing as discussed above in previously (Chapter 2), studies have shown that a number neurological conditions play a role in aesthetic activity, without firm diagnostic criteria being used throughout studies, we cannot infer that all participants (particularly those of older age ranges) have healthy neurological function with no effect on subsequent aesthetic responses.

Gender:

Within the wider field of individual difference and developmental psychology, we can see marked differences in the cognitive abilities between males and females. These can be seen across memory, creativity, problem solving, reasoning and brain activation (Bell et al., 2006). In terms of aesthetic responses however, the findings have been mixed, some finding differences between males and females and others noting the overall similarities. Whilst not of direct interest/relevance within this thesis, gender will be explored as a factor therefore a brief summary of current findings will be explored below.

Some early studies have suggested that women are more attracted to impressionist paintings than men, with men showing preference for modern paintings (Bernard, 1972). Women preferred representational art which displays soft and curved patterns were as men preferred more abstract work containing higher numbers of pointed or sharp shapes (Cupchik & Gebotys (1988). Evidence seemed to point towards aesthetic differences, or no tangible evidence of sex differences in aesthetic judgments (Farrell & Rogers, 1982; Limbert & Polzella, 1998; Lindauer, 1990). More recent studies have however reported that women demonstrate an overall higher appreciation of, and gave higher scores for, art reproduction stimuli than males (Frumkin, 1963) and that abstract art was generally rated more highly by females than their male counterparts (Furnham & Walker, 2000). Some have suggested that it may be a result of increased exposure to different types of art through technological advancements that may also influence both male and female responses.

Polzella (2000) looked at gender differences in college students for colour reproductions of art stimulus. Results found that Impressionist paintings were judged as the most pleasing by females, and also evoked relaxation and alertness. It was concluded that the differences between males and females might be a result of differences in perceptual style and emotional sensitivity within between genders (Polzella, 2000). It appears that perceptual styles or affective processing may result in significant differences in aesthetic response between genders. One study found that paintings that showed behaviour evoked more pleasure and attention among female participants over male participants (Fedrizzi, 2012). The author suggests that neuroanatomical studies can enhance the comprehension of why such gender differences appear to exist (Fedrizzi, 2000) and other evidence demonstrating gender differences in cognitive processes (Leder et al, 2004) support this claim.

Cela-Conde et al (2009) found gender-related differences in parietal activity during aesthetic appreciation and judgments. While in both sexes, activity is focused in the parietal lobe; it appears that males show lateralized right hemisphere activation in the parietal lobe while females show bilateral activity in the same region. These results could (although not expressly concluded within the paper) point towards a difference in the way males and females process aesthetic appreciation, although specifying how the differences manifest in response is challenging and yet to be explored in great depth. When looking at landscape preferences, gender differences have been found previously (Kellert, 1978; Lyons;

1983) it could be suggested that these differences in response to landscape between men and women may have evolutionary roots.

Silverman and Eal's (1992) hunter-gather hypothesis offers one possible explanation for the differences in perceptual strategies and therefore as a results, aesthetic responses. The theory outlines that gender differences in spatial ability is a qualitative result (rather than any quantitative differences) of the different tasks of the sexes in hunter-gather tasks. Spatial skills associated with hunting are more developed in males and females show heightened peripheral perception and incidental memory for locations and objects because of the gathering tasks. Further findings suggest that males look at the whole picture during aesthetic judgment, where as females tend to pay attention to smaller details within the picture (Cela-Conde et al., 2009).

As also found when exploring the investigation of Age, the literature appears to show that whilst there may be some underlying differences in aesthetic judgment across gender, particularly in terms of content, the impact of social background, experience and interest in Art is a much more powerful predictor of difference in aesthetic response (Johnson & Knapp, 1963). It is important to note that the literature within the area, in relation to making judgments about fractal patterns in limited and needs further exploration. While it is beyond the scope of the thesis to explore the perceptual and processing differences between men and women in their response to fractal patterns, the previous research will provide a good framework from which assumptions can begin to be made about the role that gender plays in preference for fractal patterns.

Personality:

Within research there is a long tradition of classifying and understanding differences in psychological experience. One such classification is the measurement of individual's traits that contribute to personality, stable traits that are consistent across various situations. Compared to other differential factors within this chapter, there is a wealth of evidence exploring the impact of personality on aesthetic judgments. Burt (1933) conducted one of the earliest studies to explore aesthetics preferences, and did this with a series of picture postcards. Participants were made up of 'normal' subjects and experts. The results revealed a 'general' factor of aesthetic judgments across all participants but further analysis also revealed bipolar factors for different types of art preference which appeared to be related to individual differences in personality. Eysenck (1940-1941) continued this line of work in later years and explored responses to different types of stimuli including pictures. His results, like Burt's (1933) found a general trend in aesthetic judgment (which he called T factor) and also a bipolar factor accounting for different preferences within art (which he called the K factor). Other studies also found this general factor and bipolar factors in aesthetic judgments (Barron, 1953; Peel, 1945; Green & Pickford, 1968).

A wide range of personality traits and measurements have been linked with preference for particular scenes, or artistic stimulus. Studies have found that Neuroticism was linked to preference in abstract art over other artistic styles (Furnham & Walker, 2001; Knapp & Wulff, 1963). Perhaps the most consistent finding within personality and aesthetic research, particularly for artistic stimulus is the characteristics of 'Sensation Seeking' and 'Openness to Experience'. Costa & McCrae's (1985) Big-5, or, NEO personality inventory classifies 'openness to experience' as a distinct personality factor. Zuckerman, Ulrich & McLaughlin (1993) explored Sensation Seeking and its relationship to nature paintings as well as complexity and tension within the image. The results found that men liked complex, high-tension realistic paintings more than women did. Additionally complexity alone did not appear to interact with personality, and this contributed the basis for not exploring personality factors within the scope of this thesis.

Sensation seeking was found to be positively related to preference for surreal art and negatively related to preference for representational art. Established measures such as the Big 5 personality inventory (Costa & McCrea, 1985) were weakly associated and it is suggested that narrower and aesthetic specific personality measures may be better predictors (Furnham & Avison, 1997). Many studies show the relationship existing, but the power of personality traits over other confounded variables were explored and findings revealed that only 33% of variance in art experience was accounted for by personality factors (specifically ‘openness to experience’), measures of intelligence and finally previous art experience (Furnham & Chamorro-Premuzic, 2004).

The wealth of evidence for aesthetic judgment and personality factors mean that the many areas, such as preference for fractal dimension have explored the personality factors that have been suggested to contribute to the differences in preference, with preference for higher D values in creative people (Richard, 2001). This result was tested further by Aks & Sprott (1996) who found that participants who deemed themselves to be creative on self-report measures, contrary to previous research, found that they had a preference for slightly lowered D values. This variety in findings could be suggested as an indication that other factors and not personality may influence the level of preference in D values.

The discussions above demonstrate strong and established links between personality factors and aesthetic judgment. Given this wealth of evidence, and lacking theoretical justification for complexity, the current thesis will not directly explore personality factors and the relationship with fractal patterns, as previous research has already explored this area of investigation, however the area remains a fruitful area for the future.

Conclusion:

As evidenced throughout the current chapter, the literature exploring individual differences in aesthetic responses was not developed from a collective body of knowledge and instead the results vary and are full of contradictory findings, which appear to be dependant on the disciplines, design and stimulus used. This means that making conclusions across the differing fields is a difficult task. New cross-disciplinary development such as neuroscience and psychology, or sociology and in the case of this thesis physics and psychology are offering new more empirically robust directions in the field. The literature explored above provides an overview the impact of cross-cultural, sub-cultural and further individual differences influences on aesthetic judgment across art, abstract empirical aesthetic stimulus as well as natural and landscape scenes. The 3 areas were looked at in conjunction as there is currently limited evidence exploring fractal patterns cross and sub-culturally. The majority of findings suggest that there does appear to be some consistencies in visual preference across cultures, particularly when looking at aesthetic responses to landscape. This offers support for existing theories in Empirical Aesthetics towards a universal pattern of preference. Further to this however, is the findings show that sub-cultural factors and previous visual experience play a role in shaping our preferences. The literature reviewed raises questions about the ‘universality’ conclusions raised in fractal aesthetics research (Spehar et al., 2003), considering the evidence is limited and still relatively unexplored. In summary the current literature demonstrates the requirement for further evidence exploring how cultural and cross-cultural factors can influence preference for fractal patterns is required before a true statement of universality can be made.

One of the strongest sources of evidence within cross-cultural aesthetics points to a generally consistent appeal for natural scenes over man-made environments, although this is not always consistent; Subsequent evidence resulted a body of research that not only shows the responses to nature, but goes beyond aesthetics. The following section will explore the implications of understanding nature and within it fractal shapes that may venture far beyond a purely aesthetics perspective and towards a framework of psychological well being and behavioural impact that natural shapes, and in turn fractal patterns may have.

5.0 Beyond aesthetics….

The following section explores the responses to fractal and complex images beyond purely aesthetics responses. As noted in the previous sections, fractal/complex images and patterns have an appeal, which spans further than purely aesthetic responses. Classifications of images, commonly of nature, have been found to promote psychological wellbeing, and positive behaviour, including environmental connectedness and even have restorative values for stress and medical recovery. Some theorists believe these responses are a result of our evolutionary history with nature, others see natural images as offering a low cognitive load and reducing stress responses. Fractal complexity and nature are inexplicably linked and this chapter will also discuss studies demonstrating that restorative responses of nature can also be seen toward pure fractal patterns. The section will end with a brief summary of the way aesthetic findings have been used in real-world applications demonstrating the power that aesthetic responses have on behaviour, attitude and beyond.

5.1 Responses to natural and urban environments: Beyond Aesthetics.

The universal aesthetic appeal of nature is well established and the rationale behind this strong aesthetic pull has been traced to our cognitive processing, evolutionary history and biological instincts. Research trends suggest two main approaches to understanding the benefits of nature, which may account for such strong preferences seen across populations.

Attention restoration theory outlined and explored by Rachel and Stephen Kaplan (1989; 1995) emphasises the role that natural scenes play in cognitive restoration, by improving attentional fatigue. Concentration was found to be improved after spending time in a natural environment (or viewing a natural environment) and it is considered a result of the effortless attention and soft draw of nature, such as watching the ripples in a pond or clouds float by requiring little attention (Kaplan & Kaplan, 1989; Kaplan, 1995). Within urban environments this effortless attention is less adaptive, actions must be inhibited, many distractions are present in the urban scene that mean attention is overstretched and eventually become fatigued. In a recent study Berman, Jonides & Kaplan (2008) extended this idea and compared the restoration effect of natural and urban environments. It was proposed, as in early findings, that natural environments capture attention modestly which allows for continued top-down attentional processing as well as bottom-up cues. Urban environment alternatively grab attention in an overt manner, leaving little attentional capacity, as the environment requires direct attention- this in turn results in less restoration effects. Their findings support this hypothesis and show that walking in nature and viewing pictures of nature significantly improve directed attention ability. It was concluded by the authors that 'simple and brief interactions with nature can produce marked increases in cognitive control" (Berman et al., 2008 p.1211). This study suggests that our preferences for natural images are shaped by more than bottom-up factors involving environmental features but in fact, whether consciously or unconsciously, aesthetic choices result from top-down processes that favour and pick out scenes with restorative qualities.

Another approach suggested for accounting for higher preferences for natural scenes use the evolutionary or biological model (Ulrich, 1983; Ulrich et al 1991) that emphasises the importance of affective functioning, such as restoration from psychophysiological stress associated with threat or challenge.

Evolutionary theory is a promising and complementary approach to aesthetics, and particularly neuroaesthetics because it attempts to explain why our brain is attuned to particular perceptual experiences. The Biophilia hypothesis, proposed by Wilson (1992) is a theory that aimed to understanding our apparent affiliation with nature and by extension, of relevance to this thesis, fractal patterns. It asserts the existence of specialist cognitive modules that are genetically based to affiliate with life and lifelike processes. The interaction with nature and natural forms is of a benefit both physiologically and psychologically. The savannah landscape or the blossoming flower produce positive aesthetic responses because of they were a markers in our genetic history of safety or food sources. Kaplan & Kaplan (1989) have continued research on the topic of landscape preference and have found that on the whole people demonstrate preference for natural, rather than built environments. Natural environments displaying fractal qualities, where as man-made built environments display (on the whole) traditional Euclidean measures. This calls into question the extent to which our evolutionary ancestry, rather than our developmental life experiences shape our preference for natural and art environments. "*The mind is predisposed to life on the Savannah, such that beauty in some fashion can be said to lie in the genes of the beholder?"* (Wilson, 1984; p.101).

Some researchers attempt to define the field as an "attempt to understand the aesthetic judgment of human beings and their spontaneous distinction between 'beauty' and 'ugliness' as a biologically adapted ability to make important decisions in life." (Hartmann & Apaolaza-Ibanez, 2010). Heerwagen and Orians (1993) state that responses to the natural environment, both positive and negative, are a product of our evolutionary instincts. We respond favourably to environments that have the most potential to keep us safe and well.

While the studies and links seem plausible, given the wealth of previous evidence, can the evolutionary approach take into account individual differences found between aesthetic judgments? In some ways yes, the hunter-gather hypothesis (Silverman & Eal's, 1992) offers one possible theory to account for differences in perceptual strategies between males and females. These findings demonstrate how some differences may stem from our evolutionary history rather than our experiences.

Discussed above are two possible theories that account for the strong preferences consistently found towards natural over urban or man-made scenes. Regardless of the foundations, there are studies that have found that these preferences may have impact beyond purely aesthetic judgment. Next we will explore some key studies outlining the potential impact of spending time in nature, the most preferred environment of most, compared with spending time in non-adaptive or cognitive damaging/disruptive environments.

Ulrich and colleagues (1991) have done extensive research exploring the potential responses beyond aesthetics that natural or urban scenes have on a viewer. In one such study, 120 subjects were asked to view a stressful movie. Participants were then shown a video of either a urban or rural environments. The study aimed to explore the stress restorative responses when encountering natural or urban scenes using both self-rate measures and a series of physiological measures to record the outcomes. Results show that recovery was found to be faster and better on the whole after viewing natural rather than urban environments.

Ulrich et al's (1991) findings opposed Kaplan and Kaplan's (1989) findings that differences occur between urban and rural environments as a result of the differences in attention and cognitive load. These findings showed no difference between classifications (urban/rural) of the scene and both elicited the same levels of attention or fascination. The results do not support the psycho-evolutionary theory as restorative responses to natural images were found to lie in positive emotional states and these changes are sustained by attention.

Following a string of fairly consistent findings for people to prefer natural over man-made built environments van den Berg and colleagues (2003) attempted to test, on a larger scale than seen previously, the role of restoration to the different environmental scenes. This study has several conclusions important to this thesis, the first is that simulated natural environments were rated as more beautiful than simulated built environments- suggesting simulated nature (perhaps containing fractal patterns) may be able to evoke these positive restorative responses that go beyond mere positive aesthetic judgments. The second important finding was that higher preferences were associated with greater affective restoration, and this effect remained strong even when scenes were statistically similar. When the restorative effect (naturalness) was removed, differences between natural and urban environments in terms of preferences where significantly reduced. The final relevant finding from this study to this thesis was that preferences for environment appear to be mediated by perceptions of the environment's potential for restoration. This is confirmed with studies that show stronger preference responses for natural/restorative stimulus when experiencing heightened stress or mental fatigue (van den Berg et al, 2003; Staats et al, 2003). We can conclude that natural environments and scenes elicit stronger restorative effects than built and man-made environments (Ulrich, 1991; Hartig et al, 1991 & 1996; Ulrich et al, 1991).

Landscape has been found to influence aesthetic appreciation as well as health and well-being responses. Velarde et al (2007) aimed to review the types of landscape used in previous studies and then unpick the impact these individual landscapes had on health effects. Their findings show that most of the previous literature classifies environments as 'urban' or 'rural' and did not attempt to explore the smaller sub-groups within these environments. Generally results supported the notion that natural landscapes resulted in stronger positive health effects when compared to urban landscapes. The authors notes the difficulty in quantifying landscape to allow stringent casual relationships to be explored in great details and all for new ways of quantifying the visual environment to further understand the health impact of different environments. Fractal dimensions offers one way to quantify natural scenes that were previously considered chaotic and unorganized, this thesis may go some way of following up Velarde and colleagues (2007) call to stringently quantify the visual environment to begin to make further progress. Fractals have already been used to quantify some aspects of the visual environment, mainly nature, and the responses beyond aesthetics have also been seen.

As discussed previously fractals characterise many of the seemingly complex visual patterns in the natural world and have been described as the "fingerprints of nature" (Taylor et al., 1999). It is considered by some that fractals (with their strong link to nature) tap into specialists cognitive modules that have developed to moderated information about living things (Wilson, 1984) and that such modules are linked with emotional regulation and reduced physiological stress (Taylor, 1999).

Similar to research exploring the impact of nature as an overall construct, Hagerhall et al., (2008) broke this down and reported that viewing fractal patterns elicited high alpha in areas of the brain concerned with attention and visio-spatial processing. Providing support for the idea that training using fractal shapes could help the development of perceptual concepts of the natural environment, stimulate Biophillic responses and trigger aesthetic interest and restorative responses (Joye, 2005; 2006).

The links span further and Taylor (2010) argued that mid-range preference hypothesis was based on evolutionary principles that the mid-range fractals are most akin with a safe and plentiful environment well equip for survival. The first author to state the preferences appear set at mid-range was suggested by Sprott (1993) and went on to be tested again in further study (Aks & Sprott, 1996), which demonstrated consistent preference for mid-range fractal patterns.

Hagerhall (2005) continued this trend and found that people judge fractal landscape silhouettes at the mid-point as most natural, demonstrating the clear link between natural processing and fractal shapes. In a later study Hagerhall et al (2008) attempted to explore responses to fractal patterns beyond purely aesthetic judgments and used EEG to measure participants responses exposed to various levels of fractal dimension. The results found that the mid-range fractals elicited processing signals associated with relaxation. The authors concluded that this response is seen because it offers the optimal chance of survival, supporting the previous conclusions made within the field (Taylor, 2010).

The literature discussed above demonstrate the power that natural and fractal images appear to have over human wellbeing, both psychologically and physiologically. This leads to questions about how these relationships can be harnessed in a positive way? Van den Berg et al (2003) concluded their paper with a warning that ignoring public preference and continual industrial development means that environments with restorative qualities are decreasing which will in turn result in negative consequences to human well-being. The next section begins to explore the potential impact of being connected with nature beyond wellbeing and towards the wider wellbeing of nature and the environment as a whole.

5.2 Connectedness to Nature:

As demonstrated in the literature in the previous sections, fractal patterns can be used to evoke responses similar to those of natural images, and as such it is important to think about the potential uses for this perceptual and psychological connection between the two. There is growing evidence suggesting that feeling connected with nature has positive psychological and physiological repercussion and as such this thesis aims to extend the current findings linking natural responses directly to fractal patterns and explore what, if anything, aesthetic judgments for fractal patterns can reveal about how connected individuals feel to nature. One aim of this thesis is to explore the differences between urban and rural participants and in addition aims to explore if preference patterns for fractal scales (such as the mid-range hypothesis discussed previously) are related to participants feelings towards nature. Feeling connected to nature has important implications for environmental attitude and willingness to take conservation action or donate to environmental causes. We will briefly highlight some key findings within this field and in addition explore how connectedness to nature can be measured and subsequently tested.

Despite the growing evidence showing nature has positive and restorative responses and that generally nature is consistently preferred over man-made environments such as urban city scenes, there appears to be great variation in the extent that individuals are drawn to and feel at one with nature. These could be related to a variety of factors including environmental experience. If you are living in an urban environment you are not commonly surrounded by nature, might this play a role? Alternatively do factors such as age or gender play a role in differences in how connected to nature individuals feel?

Why some people feel strongly about nature and others feel unmoved has been investigated in the field of environmental psychology (Kals, Schumacher & Montada, 1999) and findings show that along with several other variables, positive experience with nature (either in the present or memories from the past) can predict positive environmental behaviours.

Schultz (2000) found that the extent to which individuals see themselves as part of nature influences how likely there are to have environmental concerns. The same author in later works outlines 3 components that construct our connectedness to nature including; The Cognitive component, The Affective component, and the Behavioural component (Schultz, 2002). If people feel good about their environment, they are more likely to respect and behave with empathy towards it. It has been proposed that in modern societies we spent as much as 90% of our time indoors away from nature. This lack on contact has been considered to have a negative impact on our societies connectedness to nature and results in a less intense feelings of responsibility to protect the natural environment (Schultz, 2002).

Strong warnings have been raised that the feeling of being disconnected with nature could have potentially disastrous consequences for environment sustainability (Nisbet et al., 2009). It appears that positive interaction with nature evokes a greater liking for nature, and as such increase the chances of environmentally sustainable behaviour. This is of particular relevance to this thesis, as participants will be explored across sub-cultural environments. Including participants classified as ‘rural’ with common interactions with nature and ‘urban’ with limited interactions with nature.

Several studies have demonstrated the links between experiences with nature and behaviour in later life in terms of conservation. Wells & Lekies (2006) explored the links between childhood nature experience, views and behaviour towards environmentalism in adulthood. The study looked a these experiences in a large sample of 2,000 adults and found that childhood experiences in natural environments, particularly for ‘wild’ nature had positive results on environmental attitude in adulthood. Additionally those with wild nature experiences were associated positively with environmental behaviours whilst those with only domesticated nature activities (such as gardening interest) did not have as strong an association with positive environmental behaviour.

In a later study, Zaradic, Perhams & Kareiva (2009) found similar results that time spent hiking or backpacking in wild nature had positive correlations with monetary contributions to conservation up to 11-12 years after these experiences. This relationship is negative with those who spent time in public or domesticated land or in activities such as fishing. These results appear to show a worrying trend in decrease in experience with wild nature resulting in much less environmental identification in years to come. These results demonstrate links between sub-cultural groups that partake in nature experiences over those, most likely urban populations, who do not have these similar experiences that not only appear to have less aesthetic response as well as less behavioural response.

Given the influence feeling connected with nature appears to have on positive personal and environmental wellbeing. Researchers sought to find reliable measures with which this construct could be measured. How connected an individual feels to nature is considered as a stable construct, similar to a personality trait (Nisbet et al., 2009). Several different measures have been developed in an attempt to quantify this attitude and explore the differences between cultures and sub-cultures in their relationship with nature.

The Connectedness to Nature Scale (CNS) was one such measure, developed to explore individual differences in how emotionally connected to the natural world one feels (Mayer & Frantz, 2004). The scale was developed by environmental psychologists hoping to find a reliable and stable measure to classify how much an individual is identified with the natural world around them, and any behaviour as a result of this connection. Mayer & Frantz (2004) found that an individuals CNS score is a significant predictor of subjective wellbeing and ecological behaviour. The measure is brief to distribute and have been found to be reliable and stable as a psychometric test.

Other scales such as Nisbert et al's (2009) 'Nature Relatedness' scale have also been tested and found to be valid methods of exploring individual affective, cognitive and experiential aspects of connection to nature. Nisbet and colleagues (2009) also found that feeling connected with nature has multiple benefits such as resulting in positive moods and less negative moods. This results mirrors the findings of Mayer & Mcpherson-Frantz, (2009) that exposure to nature and feeling connected to nature provides many benefits to psychological and physiological wellbeing.

Based on the findings discussed in previously sections it would be expected that urban participants demonstrate less connection with nature than their rural counterparts, related to this previous research finds that positive past or present experiences of nature predict how connected an individual feels (Kals, Schumacher & Montada, 1999) however the relationship between nature connectedness fractals is as yet unknown.

In earlier studies, this idea is noted by both Ulrich (1974) and Shafer & Mietz (1969) discussed the aesthetic benefits that can be of considerably importance. Individuals appear to want to protect what we find aesthetically pleasing therefore with a growing urban and industrialisation does the future point towards the work of Nisbet et al., (2009) who warned that loosing connection with nature means loosing those who want to protect it?

As discussed, outdoor visual environment can influence an individual's psychological wellbeing. Responses demonstrate that visual landscapes are important beyond a purely aesthetic point and in fact influence emotive states. In the field of psychology and other disciplines we need to explore these implications, not just how we can benefit from nature, but also how we can prevent negative responses to high-stress environments in workplaces, hospitals, schools, and living locations? If nature promotes wellbeing, Ulrich (1979) asked, "what man-made forms, textures and materials evoke responses similar to those in nature elements?" Could fractal patterns offer the answer?

We have seen that aesthetic responses to nature and perhaps fractal patterns can have wider implications than merely preference responses. While this is the case for nature, many other fields have noted the potential ways that aesthetic research can be used to promote particular behaviours, including positive environmental behaviour as discussed above. The following section will give an insight into the ways aesthetic responses are currently being used in the applied field to demonstrate that aesthetic judgments go beyond pure preferences but instead can have important psychological and behaviour implications.

5.3 Current applications of aesthetic research:

The next section moves away from purely natural and evolutionary theories of aesthetics and gives some examples of the application and responses of aesthetics in Architecture, Retail and finally Website Design. The section outlines the psychological and behavioural responses to visual environment across 3 different, but common, daily experienced environments.

Architecture & interior design: psychological and physiological responses:

Our visual environment, particular in western industrial society is dominated by architectural space, whether the landscape and city designs, the house in which we live or the building or the locations in which we work, rest and socialise. Like Art, Architecture for a long time has applied intuition and inspiration to design.

Around the early 1990's there was a push toward empirical investigation of the architectural factors that can influence on our wellbeing and psychological and physiological reactions to that space. Some research believe that architects planned and designed space that was fit for practice and purpose, but paid little attention to the psychological impact these designers where having on those within (Ulrich, 1991). Evidence demonstrated that poor design had negative psychological impacts, demonstrating it is not just a case of better designing would see improvement psychological wellbeing but that some trends were actually harming viewers (Ulrich, 1984).

Factors in the built architectural environment such as windows, flow and decoration can have significant impact of psychological and physiological wellbeing. Workplaces that are windowless can be stressful to psychological health and as a consequence are disliked (Heewaseri & Orian, 1986; Farley & Veitch, 2001; Veitch & Gifford, 1996), thus demonstrating the links between aesthetic responses as a predictor of psychological and physiological wellbeing within a built environment. This relationship can be seen in both directions, as further research has found that living in a home that you and others judged as attractive produces heightened positive psychological effects (Stamps & Nasar, 1997). So individuals appear to like things because of the positive psychological effects they have, but liking something initially (immediate aesthetic response) can also produce positive psychological effects.

One specific area of interest to psychologists and architects relates to institutional environments such as hospitals or prisons, and a wealth of evidence has been collected to explore the consequences that architecture (and their contained aesthetic features) have on psychological and physiological well-being. Within prisons, cells with a window that look out onto natural scenes, over cells with a window that looks out over man-made scenes have reported lower levels of stress and had recorded less sick calls (Moore, 1982, West, 1986) showing the potential impact of architectural features on everyday psychological wellbeing.

Within a hospital setting, research has shown significant positive improvement in well-being over a variety of interventions within clinical settings. Interestingly, heart surgery patients felt less post-operational stress after interior design intervention of natural or abstract art exposure (Ulrich & Lunden, 1990) however these results should be read with caution as the study lacked a control group from which comparisons cannot be made. Other studies have found that nature murals (over blank walls) can reduce patient stress in a dental clinic (Heerwagen, 1990) or ceiling mounted pictures displaying serene over arousing images produce positive physiological responses (reduced systolic blood pressure) in stressed patients (Coss, 1990). These few studies represent the tip of the iceberg in the field that have explored both larger and smaller scale architectural and design interventions that have positive effects on patient or inmate well-being. In a comprehensive review of the data, Ulrich (1991) concluded that health-related effects of good design show that it can be related to reducing cost of healthcare. These findings also point to bad design as a hindrance to wellness and the results overall shed light on the importance of awareness of good health care design to improve psychological and physiological wellbeing.

Conclusions should be made from the findings that well considered and empirically sound design goes some way to support residents and facilitate both psychological and physiological wellbeing. Aesthetic responses maybe our evolutionary/biologically bound method of distinguishing environments that can produce positive and negative responses, which would add credence to theories such as the Biophilia Hypothesis (Wilson, 1984).

Retail, Sales and Environmental Aesthetics:

The primary purpose of understanding the retail environment and the impact of aesthetics (among other factors) on consumer behaviour revolves around the potentially significant economic and business implications. Whilst the link between environment and consumer behaviour has been noted in the past and changed in an anecdotal fashion by managers, Bitner (1992) noted that these changes to evoke particular consumer responses had not been based on empirical evidence up until that point.

In 2000, Turley & Milliam conducted a review of 30 years of evidence exploring the ‘atmospheric’[1] effect of shopping behaviour. There results offered an interesting overview of the field, they also explore behavioural responses to store environments. The Approach- Avoidance consumer response (Mehrabian & Russel, 1974) was discussed as a result of environmental features. Turley and Milliman’s (2000) review concluded that managerial staff should be taking note of current research in the field as store environment, covering a wide range of perceptual input can have a significant effect of sales, with 25 from the 28 studies reviewed demonstrating sales differences dependant on store environment, as well as approach over avoidance behaviour. The review also highlighted the impact of individual differences, therefore authors conclude that store environments should be targeted to specific audiences dependant on age and gender.

More closely related to the work within this thesis, Gilboa & Rafaell (2003) conducted an exploration of environmental features in retail stores and responses. The study aimed to measure the influence of grocery store environments on emotions and behavioural response, and was the first to test empirically the approach-avoidance response to complex scenes. Of most interest to the authors was the impact of complexity and order in the visual environment and the resultant approach-avoidance response linked with positive consumer behaviour. Results found support for Berlyne’s inverted-U response to complex stimulus, with stimulus falling within the mid-range (with visually complex scenes containing some level of order) evoking significant approach behaviour. These finding support current literature within the wider field of environmental psychology in which environments of moderate complexity and high order show the highest levels of approach behaviour (Nasar, 1987; Herzog, 1992). The findings highlight the importance of examining visual factors such as complexity in the context of retail environments and demonstrate the links between low-level aesthetic responses and behaviour. It confirms and validates the use of complexity as a measure of environment and suggests behavioural predictions can be made on the basis of these features.

Aesthetics, Website Design and Usability:

Recently there has been a growing wealth of studies exploring the aesthetic qualities of website design and the subsequent responses beyond the aesthetic. Attention, usability, frequency of use, likeability, credibility and likelihood of purchasing from site are several possible results associated with aesthetic responses to website design (Chen, 2009). These, amongst other factors, will be explored briefly in the following section to demonstrate the way aesthetic responses can influence behaviour and attitude to webpage interaction, an increasingly important field given the growth in the use of the internet in modern society.

In a widely cited study, Tractinsky et al., (2000) found high correlations between perceived beauty of ATM's and the users perceived ease of use of the ATM interface. This was one of the first studies to find experimental support for the 'beautiful-useful correlation'. The results in additional went further to find that even post-use perception of usability was positively affected by the aesthetics of the interface and not actually by the usability of the system. This study demonstrates the power of aesthetic appeal on other perceived attributes.

A review by Tuch et al., (2000) offers a succinct overview of the field of aesthetics and Human Computer Interaction (HCI). They found that most studies found moderate to strong correlations between perceived usability and perceived aesthetics. These findings should be approached with caution, as there are limited inferences to be made about the direction of the relationship in correlational studies. Tuch et al., (2000) also reviewed the findings of a series of experiments investigating aesthetics and usability in websites and other human computer interfaces. The results of this review showed the notion 'what is beautiful is usable' was only partially supported with empirical evidence and in specific cases 'what is usable is beautiful' was supported. Findings show that 3 from 5 studies reviewed showed significant effect of usability and aesthetic quality.

In a follow up study Tuch et al., (2010) explored the relationship between usability and aesthetic response further in a lab based study exploring different versions of an online shopping website. There results found that aesthetics does not have an impact on perceived usability, but usability does significantly effect aesthetic ratings. This study shows that factors above and beyond aesthetics can have significant influence on post-ratings of aesthetic judgment.

Gender differences can also be seen in website design, a strong symmetry effect was found on preference for web pages, however this effect is only seen in male participants, but no such positive of negative reaction towards symmetry/asymmetry seen by female participants (Tuch et al, 2010). This highlights the need to acknowledge and target visual environments to particular target groups to ensure the highest positive response and sought after behaviour, in this case perceived usability.

The results from the field, as outlined briefly above, have been and continue to be used in implementation and design decision for particular target audiences. A variety of difference disciplines have connections with aesthetic research and whilst there is predominantly separation, reviewing the literature highlights the potential for cross-disciplinary collaboration to really demonstrate the power that aesthetics have over our psychological and physiological responses to a variety of daily and novel situations.

Conclusions:

This section has explored some of the potential responses that go beyond studying a purely aesthetic responses in research. It demonstrates the power that nature and natural shapes can have our individual psychological and physiological wellbeing, it also explores how these responses can be mirrored using man-made stimulus such as art or fractal patterns while evoking the same response. The links between natural patterns and connectedness to nature will be explored within this thesis in an attempt to make links with both aesthetic and environment responses to fractal patterns. From the evidence it is clear that understanding aesthetic responses to nature and how connected these aesthetic responses make us feel to the natural environment can have important implications on environmental sustainability. This section also outlines how the findings of this thesis fit within the multidisciplinary field of aesthetics and environmental psychology as well as laying the groundwork for potential next steps with the results. Results from the field have been and continue to be used in implementation and design decisions for particular target audiences. This section has demonstrated some of the foundations of aesthetics theories and their application in real-world situations. It has shown the importance of studying the field of aesthetics, demonstrating how these basic visual processes can have much wider impact than only preference responses. Research has shown that responses can span to attitude, reaction and even behavioural changes in individuals and as such warrant further investigation.

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[1] Atmospheric is the field specific term for retail/store environment (Turley & Milliman, 2000) *findings fit within the multidisciplinary field of aesthetics and environmental psychology and lays the groundwork for potential next steps with the results.*

6.0 Rationale & Methodology:

The following section outlines the research questions, rationale and hypotheses to be examined within this thesis in an attempt to add to the currently limited field of research exploring aesthetics responses to fractal patterns. This chapter will also specify the methods adopted in the thesis and the rationale behind these methodological choices. The methodology section will first explore the different types of established methods for measurement of aesthetic judgments/responses, secondly will explore the stimulus used within the study, the chapter will then examine the different methods to analysing complexity and fractal dimension. Finally measurements of 'connectedness to nature' will be discussed as a way of taking the research in an applied direction.

6.1 Rationale Summaries

Study One

Fractal Dimensions and Visual Complexity: An interrelated concept?

Visual complexity and fractal dimension have been considered distinct fields of perceptual stimulus, however this study aims to explore the relationships between the two related concepts. Study one of this thesis explores the relationship between the fractal stimuli and their associated fractal dimension (FD) developed for use in this thesis to measures of computational visual complexity obtained by analysing the fractal stimulus using the GIF ratio compression technique.

Study Two

Cross-cultural comparisons between UK and Egypt samples: Rating Scale Method

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The aim of the second study used UK and Egyptian samples in a bid to explore cross-cultural preference for fractal complexity in addition to recreate Souief & Eysenck's 1971 study exploring differences in complexity across the two cultures. Souief & Eysenck's previously found that British people (with no art training) preferred complex figures but Egyptian people (with no art training) preferred the simple images. As visual complexity is significantly related to Fractal Dimension (FD) this study aims to test this hypothesis with new and improved methods of quantifying complexity. Eysenck and Souief (1971) did not believe that their data supported large aesthetic differences between cultures but instead believed that the findings point towards a universal preference and to unpick these findings further. The second study within this thesis considers the response of UK and Egyptian samples to fractal complexity and if this trend would follow the same pattern. The aim is to explore in greater detail the impact of country/culture on visual preferences for fractal patterns.

Study Three

Validating the mid-range hypothesis for fractal preference

This study aimed to re-test an established theory of fractal preference, the mid-range hypothesis established by Taylor et al (2001). Taylor and colleagues found evidence that preferences for fractal patterns consistently fall within the mid-range of the fractal continuum (D1.3-1.5). With lower preferences being shown for the images at the higher (D1.7-1.9) or the lower end (D1.1-1.2) of the fractal continuum. To allow comparisons to be made and validate the current established thinking, study three also introduces two further models to understanding preference for fractal complexity including a linear model of preference (with a directional relationship) as well as an equalised-mid model (systematic grouping of fractal dimension instead of lower end weighing in Taylor's model) to explore how well each model fit the preference data. The study adopts an online design, allowing participants from different countries and cultures to complete the study. This study aims to test if the mid-range preference hypothesis is stable across a wider international and cross-cultural sample adding support from Taylor and colleagues conclusions. Within the field there was a great need for the study, as so far the samples within the field of fractal aesthetics have been limited to WEIRD samples (Henrich, Heine & Norenzayan, 2010) meaning that the majority of data collection is done on Western, Educated, Industrialised, Rich and Democratic populations- it is the view of this author that if assertions are to be made about the universality of preferences, it is important to explore this from a cross-cultural and more varied sample.

Study Four

Optimal Fractal Preference; Stability across culture and within sub-cultural visual environments

Following from the cross-cultural differences found in study three. Study 4 aimed to explore if sub-cultural factors could be a powerful predictor of differences in preferences found in previous literature (see chapter 4). This study aims to explore not only a greater controlled cross-cultural sample but also explore sub-cultural differences looking at the differences between urban, rural and suburban classifications of the visual environment. Previous literature has found differences between aesthetic judgments of those living in Urban and Rural backgrounds, in addition the Mere-exposure hypothesis would suggest that the environment in which we live influences preferences. It is therefore hypothesised that the classification of a person's environment can change preferences for peak level of fractal complexity. As those living in rural environments viewers are exposed to a high number of fractal and complex natural patterns it is proposed highest preferences will be reported for high FD/complex images. Alternatively those living in urban environments are exposed to mainly Euclidean and man-made shapes opposed to natural and commonly fractal patterns, therefore it is proposed preferences for higher complexity will be lower than the rural group.

Study Five

Connectedness of Nature & Environmental Classification

This study aimed to explore if our aesthetic responses to fractal patterns is related to how connected we feel to nature. Results of previous studies within this thesis suggest that individuals living in rural environments demonstrated higher preference for higher complexity/fractal patterns than those living in urban environments. Previous literature exploring landscape and aesthetics has shown that the environment in which we spend time and see regularly governs our preferences. It is proposed that this difference in aesthetic judgment may result in differing opinion in how connected we feel towards nature. The study aims to explore if preference towards complex fractal patterns based on visual experience goes further than purely aesthetics response and instead has additional impact beyond aesthetics such as how connected, and as a result how likely we are to protect the natural environment.

Study Six

The relationship between Lifespan, Culture & Gender as predictors to Fractal Preference

The study aimed to explore the strength of the individual differences Age, Continent and Gender on preference for fractal patterns. Each was found as significant predictor model of preference in the previous studies with this thesis. Study 6 examines a combination of the entire data and one additional small set of 'elderly' participants to test the reliability of the age effects across a wider sample. Previous landscape research suggests that younger people have higher preference for busy and complex environments where as elderly people show less preference for 'wild' nature. Does this mean less preference for fractal patterns? The wider sample of participants allows more reliable contrasts between continents. This study aims to further test the complexity and mid-range models of fractal preference explored throughout previous studies within this thesis.

6.2 Hypotheses Table

Table 6.1- Thesis Hypothesis Table

Study One	**Fractal Dimension a component of Visual Complexity?** It is hypothesised that the fractal stimulus images used within the thesis will correlate significantly to GIF compression ratio scores; a computational measure of visual complexity. If confirmed this finding would suggest that fractal dimension can be considered as a related component or sub-component of visual complexity.
Study Two	**Cross-cultural Difference in Fractal Preference?** Mirroring the samples of Souief & Eysenck's 1971 study exploring the cross-cultural stability of aesthetic preference with UK and Egyptian participants, this study hypothesises that responses for fractal patterns will demonstrate cross-cultural differences for non-art training participants. The study also hypothesises support the mid-range hypothesis with highest scores being awarded to images that lie within the D range of 1.3-1.5.
Study Three	**Re-testing the Mid-Range Hypothesis in Fractal Preference** • It is hypothesised that the overall frequency patterns of preference would display inverted-U shaped function, with heightened preference at the mid-range (D1.3-1.5). There are three different models of aesthetic patterns explored in this study and as such three different experimental hypotheses: • It is hypothesised that the variables Country, Age and Gender would significantly predict the mid-range model of preference

	more so than the null model. • It is hypothesised that the variables Country, Age and Gender would significantly predict linear the Complexity model of preference more so than the null model. • It is hypothesised that the variables Country, Age and Gender would significantly predict Equalized Mid model of preference more so than the null model.
Study Four	**Cross & Sub-Cultural Differences in Fractal Preference** • It is hypothesised that the overall frequency patterns of preference would display inverted-U shaped function, with heightened preference at the mid-range (D1.3-1.5). There are three different models of aesthetic patterns explored in this study and as such three different experimental hypotheses: • It is hypothesised that the variables Country, Environment, Age and Gender would significantly predict the mid-range model of preference more so than the null model. • It is hypothesised that the variables Country, Environment, Age and Gender would significantly predict linear the Complexity model of preference more so than the null model. • It is hypothesised that the variables Country, Environment, Age and Gender would significantly predict the Equalized Mid model of preference more so than the null model.

Study Five	**Environment, Fractal Complexity and Connectedness to Nature** • It is hypothesised that the overall frequency patterns of preference would display inverted-U shaped function, with heightened preference at the mid-range (D1.3-1.5). There are two different models of aesthetic patterns explored in this study and as such two different experimental hypotheses: • It is hypothesised that the variables Connectedness-to-Nature Score, Environment, Age and Gender would significantly predict the mid-range model of preference more so than the null model. • It is hypothesised that the variables Connectedness-to-Nature Score,, Environment, Age and Gender would significantly predict the Complexity model of preference more so than the null model.
Study Six	**Lifespan, Continent & Gender- predictors of fractal preference?** The final study combines all 2A-FC design data from this thesis with the addition of a sample of older participants responses. • It is hypothesised that the overall frequency patterns of preference would display inverted-U shaped function, with heightened preference at the mid-range (D1.3-1.5). There are two different models of aesthetic patterns explored in this study and as such two different experimental hypotheses: • It is hypothesised that the variables Continent, Age and Gender would significantly predict the mid-range model of preference more so than the null model.

- It is hypothesised that the variables Continent, Age and Gender would significantly predict the Complexity model of preference more so than the null model.

6.3 Methodology

6.3.1 Measuring Aesthetic Preference:

Within the field, there are different established methods of measuring aesthetic judgment. There is vast variety within the field between the ways that researchers try to tap into aesthetic judgments of their participants. While this variety has continued to develop and grow the field often researchers do not outline clearly their rationale behind methodological choices (Augustin et al., 2012; Faerber et al., 2011). In an attempt to avoid this pit-fall, the following section will explore some the different methods used to elicit data about aesthetic judgment and justify the choices made within this thesis. Palmer, Schloss & Sammartino (2013) reviewed the current states of aesthetics and human preference, this paper provides a thorough summary of the methodological issues when measuring aesthetic responses. The section will use their outline as a structure from which to further explore the methodological choices available and used in the field.

Ratings:

Scales such as the likert scale (discrete) or line-mark rating (continual) methods is perhaps the most common way of eliciting aesthetic responses. The method allows researchers to show participants a series or single image allows collection of individual ratings for each based on a large sample. This method benefits from being able to collect data for a large number of images from a large number of participants in a short period of time, it is also a relatively simple task that can be altered to fit with the specific design, for example the vocabulary used when collecting scores is variable to include ‘liking’ ‘beauty’ ‘preference’ or behavioural choices such as ‘how likely would you be to visit this place’, ‘how likely would you be to buy this product’. This versatility means likert scales are widely used across various discipliners and research fields therefore results gathered this way can be comparable to others of similar design. Despite its wide use and versatility, problems can occur with consistency in scoring when using the rating method, particular at the start of trials. It has been suggested to over come this issue, that a full range of stimulus should be shown to the participant ahead of rating therefore allowing participants to anchor responses in preferences ahead of the trials (Palmer et al, 2013). Other potential issues with this approach include the variance with scores between participants, there are trends of ratings with some choosing extreme ends of the scales and others being more modest with their scores, or clustering around the mid-points of the scale. We cannot truly conclude that the extreme scores show extreme preference responses more so than the modest responses. It must be acknowledged that choices made may be indicative of context or individual differences approach and personality differences in which the ratings are made (Ogden & Lo, 2011).

Scored from 0 to 10, how much do you like the above picture?
(0 meaning extremely dislike, 10 meaning extreme like)

Figure 6.1-Example Fractal stimulus

Ranking:

Rank ordering methods commonly involve a participant being given a set of stimulus to order from most to least preferred. The average rank given to each stimulus across the study is calculated and used as a measure of overall preference. The task is simple and something that is commonly experienced in daily life decision-making. Researchers believe that rank ordering offering a more reliable and valid measure than rating individual stimulus alone, and this is especially marked when pairwise ranking is used between 2 choices (Hochberg & Rabinovitch, 2000) as seen in the 2A-FC design discussed below.

While this method offers good and robust methods of collecting data, with the stimulus used consisting of 81 images, allowing participants to rank order these images for preference would be a difficult, complex and time consuming method of collecting preference data. Therefore ranking was not considered usable within this thesis.

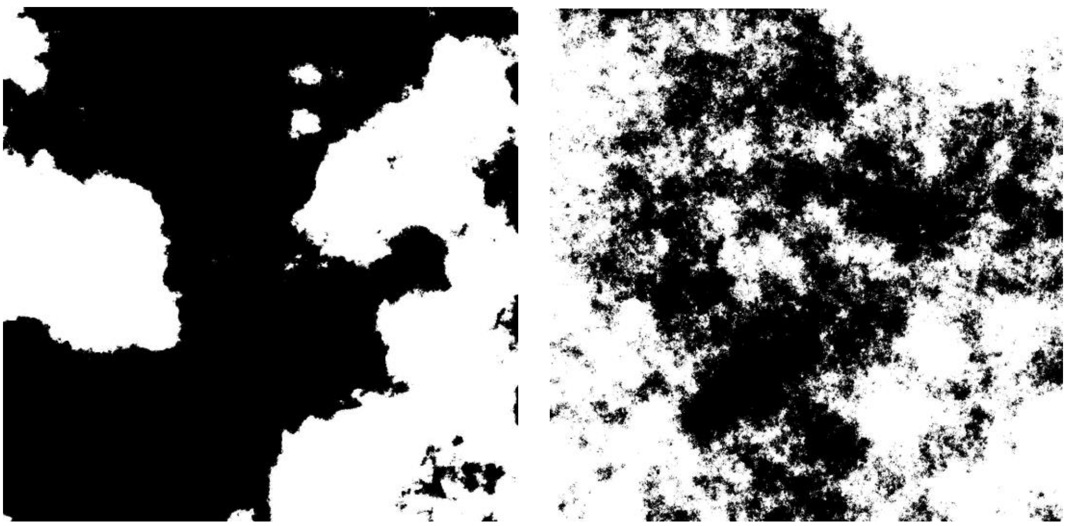
Please order these images 1^{st}, 2^{nd} & 3^{rd} in order of preferences. (1^{st} = most liked, 3^{rd} = least liked)

Figure 6.2- Example of 'order' aesthetic methodology with fractal stimulus.

2A-FC- Forced-choice:

From ranking a series of images, the forced choice method allowed the same process with smaller numbers of stimuli. Commonly the pairwise or two-alternate forced-choice method is used to unpick aesthetic responses. This method mirrors many behaviours in everyday life decisions in which we make preference choices for a variety of different situations including which station to have on the radio or which piece of art to hang on our wall. Given this task is a commonality in daily experience, it is a relatively simple and understandable task for participants. The 2A-FC method was first used by Gustav Fechner (1860) during the first recorded empirical study of aesthetics; during this study participants were asked to choose from 2 version of Holbein's 'Madonna'. This method has been found to be particularly beneficial if the images are not overtly beautiful, therefore 'beauty' or 'preference' ratings or scores are unlikely to be accurate as they would be if using artistic or realistic photographic stimulus as used in a large range of studies. An alternate-choice design allows exploration of aesthetic preference and threshold specific information. Using a forced choice method allows regression models analysis, which can provide predictive or probability statistics for the likelihood of an aesthetic choice to be made.

The method could be critiqued for its inability to offer the magnitude of preference for the stimulus. If participants are making choices between two images, using this method it cannot be verified that a participant's choice based on the stimulus being aesthetically pleasing rather than choices being based on strong/moderate dislike for the image not chosen. Despite the limitations, the findings offer one of the most controlled and suitable methods, and as such will be used (in conjunction with 1 ratings study) within the current thesis.



Which image do you like most? Tick/click/mark the one you like the most.

Figure 6.3- Example 2A-FC methodology with example fractal stimulus.

Production method:

The production method is a lesser-used method for exploring aesthetic responses. The method involves participants changing parameters in the image, whether that is the colours, shape or content of an image to explore individual's ideal aesthetic worldview. The method is limited in participants artistic abilities and confidence, people are sometimes asked to draw or create something that appeals to them, their artistic talents or methods may not produce a piece that is aesthetically pleasing to them or others. Stimulus manipulation is a technique that has been used to develop the production method in aesthetic research and in recent years Chris McManus (UCL) have began using this method to crop photographs (McManus et al, 2011) or alter the proportions of Piet Mondrian's (See Figure 6.4) painting to meet 'optimal' aesthetic experiences for the viewer. This adaption addresses many of the previous issues faced with the method and is enabled with new developments in technology. The current thesis uses a set of pre-defined fractal images controlled for FD, given the development of this took place ahead of collection, the stimulus do not currently allow this method to take place, therefore the production method was not included within this thesis as a method.

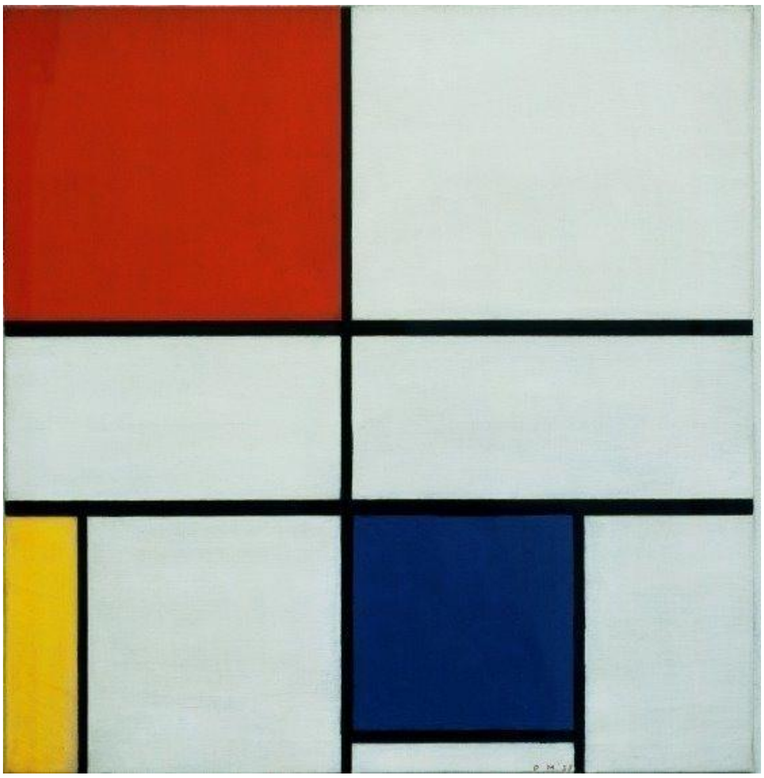


Figure 6.4- Piet Mondrian (1935) Composition C (no' III) with Red, Yellow and Blue.

Physiological & Neuroaesthetics Measures:

The above methods have been useful in providing a wealth of evidence exploring aesthetic response to a variety of stimulus however all self-reported measures are limited with human judgment bias. Studying self-report behavioural methods which are open to error therefore, with ever increasing developments in technology, researchers have began to use other techniques to measure human responses to stimulus while avoiding the potential bias or errors from self-report measures. There are a variety of ways to infer preference using physiological measures; Galvanic skin response, Heart rate, Eye movements, EEG and fMRI are just a selection. These measures allow us to explore further than behavioural judgments and infer the potential physiological responses to a variety of stimuli. These methods have been used in collecting information about potential restorative and negative responses to particular visual patterns. Despite success in quantify physiological response to fractal patterns (see chapter 5 for discussion), particularly in terms of stress reduction of restorative qualities, the use of such methods are beyond the current scope of the current thesis.

While the power of these methods are acknowledged, this thesis intends to lay the groundwork for further exploration of fractal aesthetics. At the present time, not enough behavioural studies have been complete using such pure stimulus as to allow further physiological or complex technological methods to be supported with valid hypotheses. The benefits of uses computer generated pure fractal patterns within this thesis means than unlike previous studies confounded with additional variables (such as colour, familiarity or content) the present thesis explores only aesthetic responses to fractal patterns. Many studies have used artistic or figurative stimulus and measured aesthetic judgments alongside fractal dimension. While these yield interesting findings, the stimulus used include a wealth of information above and beyond only fractal dimension which is difficult to unpick. In addition, many of the stimulus sets analysed in previous literature contain non-fractal material alongside fractal material, and while certain measures have been validated to be used across fractal and non-fractal images (See Williams PhD Thesis 2012) these cannot make strong assertions about the responses to fractal patterns alone. For this reason, much of the previous research on fractal dimension are confounded with other aesthetic variables, to move forward within the field it is important to unpick each factor and its contribution to aesthetic judgments. The present theses use of computer generated fractal patterns means that strong claims can be made about the aesthetic responses to the most basic form, and from these analysis we can be sure that the finding are related to fractal dimension (and perceived visual complexity) alone.

6.3.2. Fractal stimulus & Measuring Complexity

The Stimulus: Professor Richard Taylor and Colleagues from the University of Oregon, USA, developed the stimuli sets used within this thesis (See Figure 6.5 for example). The patterns were generated using a mid-point displacement technique, which allows generation of fractal images, by manipulating the core image and controlling for 9 levels of fractal dimension. This control ensures a complete range of fractal images are developed from very low, to very high and set point between to accurately represent to full range of fractal patterns. This control over a full level of fractal dimension (from a core image) was an essential requirement of the stimulus as the lack of full range has been suggested to account for some of the variance found within the optimal preference in early fractal aesthetics studies.

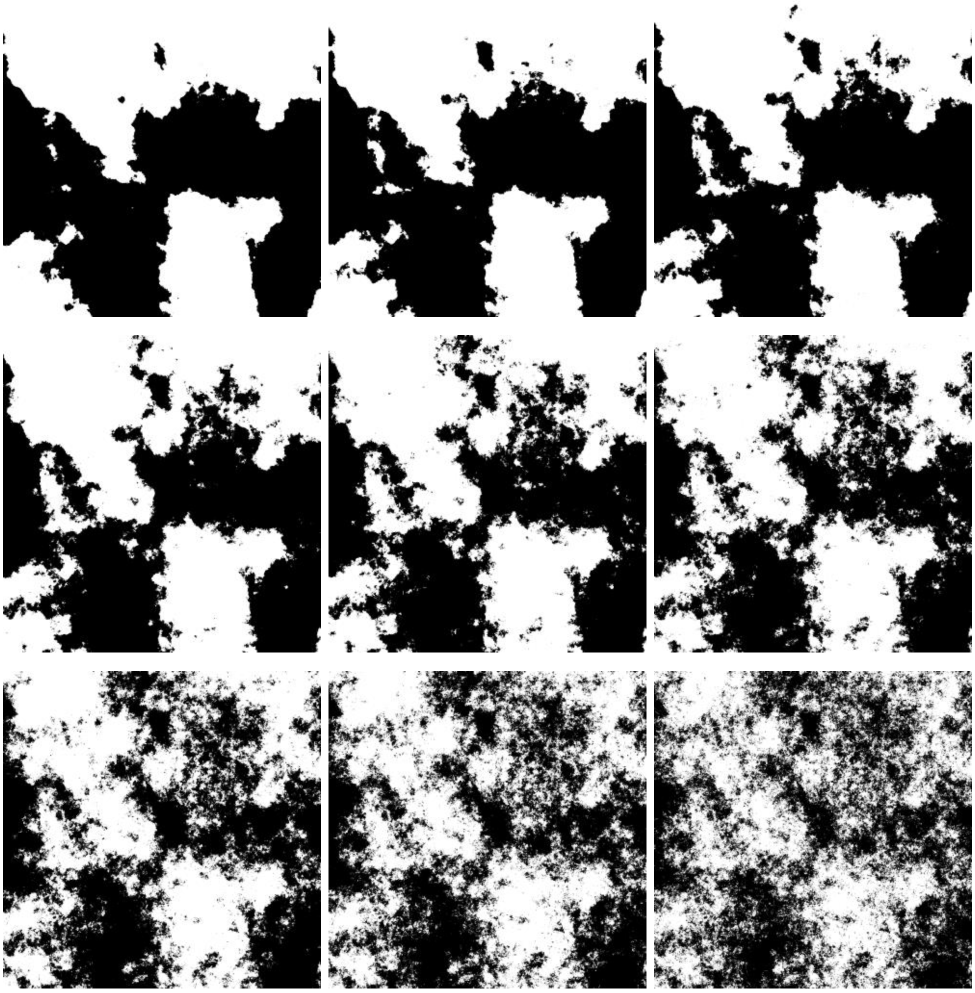


Figure 6.5- Example full computer generated fractal patterns.

When exploring the aesthetic response to the fractal pattern with the linear mixed-effect models 3 different models (and grouping of the images) will be tested. They are outlined below.

The Mid-Range Hypothesis: Richard Taylor and colleagues in a series of studies (Taylor et al., 2009;2011) found evidence to suggest three groups within the fractal continuum that appear to have significantly different aesthetic responses. Taylor et al outlined the peak preference lying within the 'mid'-range of fractal dimension, which they defined, as 1.3-1.5 and distinguished 2 other groups, 'low' 1.1 & 1.2 and 'high' 1.7-1.9 which were preferred less over the images falling within the mid-range.

The Equalised 3 Level Model: An alternative method of distinguishing the grouping could be an equalised model which still demonstrates 3 categories of fractal dimension; within an equalised model these are low (1.1-1.3), mid (1.4-1.6) and high (1.7-1.9). As the first study within this thesis attempts to explore if Taylor and colleagues 'mid-range' hypothesis is an accurate classification of aesthetic responses to fractal patterns, and alternative but similar classification was developed to allow strength comparisons to be carried out.

Binomial Complexity grouping: The final distinction between levels of fractal dimension during analysis will be classifying the images as more or less complex than it's paired comparison image. Within this grouping, a higher fractal dimension is representative of a image of higher complexity, therefore analysis will be done exploring if choices are made between the higher or lower images in terms of visual complexity. This link between fractal dimensions has been discussed in previous chapter (chapter 3) however this thesis aims to quantify this relationship statistically. To explore if this categorisation is representative of visual complexity (as well as fractal dimension) the thesis stimulus will be measured using computational complexity compression measures which has been demonstrated to provide reliable measures of human judgments of complexity (Forsythe et. al., 2008) in Chapter 7.

Measuring visual complexity:

To assess the classification between fractal dimension and visual complexity for the stimulus used within this thesis comparisons were made between fractal dimension and computational measures of complexity (GIF).

Computational measures of complexity have been used to quantify the visual complexity of many different stimulus including art, abstract patterns or realistic photographs. Measuring the visual complexity of a stimulus differs significantly from measures of fractal dimension that explore the roughness and underlying order or self-similarity of an image. Visual complexity, with compression measures, takes into account the whole of the image (rather than only fractal complexity) and compression breaks the whole image down to composite parts depending on the amount of information within the image. The resulting compression information becomes a string of symbols representing parts of the image including elements, shapes, contrasts and colours. The generalized method means that complexity compression measures can be widely applied to different stimulus sets; the same cannot be said for fractal measurement techniques as although the methods will provide a score for fractal dimension (for example using the box-counting method) for any image analysed, these cannot always be considered reliable when measuring non-fractal images.

GIF Compression: The GIF compression ratio provides a measure of the size of an image after compression and this is divided by the original size of the image (in .BMP format). This method was chosen over other computational compression measures such as JPEG as it works best with mono-chrome and geometric shapes over photographs or art scan which are better suited to JPEG compression techniques. The analysis between fractal dimension and the computational measure of visual complexity will be discussed in the following chapter (see Chapter 7).

Stimulus Summary:

Fractals offer a way of selecting one of the many facets of visual complexity and by using pure fractal stimulus we can truly explore the role this plays on visual judgments. The stimulus are a ‘pure’ form of fractal dimension and allow real and controlled predictions to be made about aesthetic responses to fractal patterns, more so than previous studies have been able to do with other stimulus. Although the application could be seen as less ecologically valid than the use of other stimulus include art or photographs, the use of pure fractal images allow assertions to be made on the basis that judgment are based on fractal dimension and visual complexity alone rather than any other variables that have been found to powerfully influence aesthetic preference such as familiarity, meaningfulness and colour.

Images selection (2A-FC Design):

The images were developed as detailed above. In total there was 9 sets of 9 images developed by Richard Taylor and colleagues. To run a full forced-choice design this would involved comparing all 81 images to each other, resulting in 6,480 possible pairs. This amount of forced-choice pairs is obviously not a feasible number of pairs to ask participants to rate.

In a bid to make the design more usable when faced with a large stimulus set, Prof Chris McManus from UCL developed a method of reducing the number of pairings required when using a forced-choice design in aesthetics research (C McManus, 2009). McManus’s method samples an entire range of stimulus but also provides detailed information on closely similar rectangles. Established analysis of 2A-FC involves summing across each column when using complete paired comparisons. McManus champions the use of a regression model approach in which dummy variables allow comparison of the preference.

McManus’ study justified a modified method of 2A-FC and this thesis developed a further modification to the traditional design. The method adopted was justified because Taylor et al (2011) found no significant differences between aesthetic response patterns to the different sets of fractal images set (developed in the same way to those used in the current thesis) demonstrating it can securely be assumed that the fractal dimension, rather than any other individual structural differences that contributed to aesthetic findings.

The pairing matrix below (Table 6.2) demonstrates how the images for each pairing were chosen. Each stimulus set included 9 images, which would result in 81 pairs per set. As literature demonstrates the presence of 3 distinct groups of fractal dimension, ‘Low’, ‘Mid’, ‘High’ the images were grouped to match the current findings, comparisons were not made between fractal patterns falling within the same group. This reduced design resulted in 26 potential pairing, and because of the number of sets two pairs allowing a variety of sets to be used. The individual images selection was done using a (quasi) randomly assigned design. For each pair, the stimulus sets were labelled 1-9. Using a random number generator the FD paired comparison was made up from one image (matching the required Fractal Dimension outlined in the matrix) from the first randomly selected set and a second image selected using the same method using a different set. A quasi-random design was chosen to avoid repetition of sets within each category.

This modified design meant that there was an equal chance and probability of participants choosing each fractal dimension point within the scale. Therefore allowing judgments to be made about differences in preference between the 3 fractal groups (low, mid, high) and complexity scales (higher or lower complexity).

The design outlined above was used for studies 3, 4, 5 and 6 of this thesis. The same selection was used in each to allow an overall comparison of the sample in the final stages of the analysis within this thesis. A regression model analysis was developed in addition as advocated by McManus (2009).

Table 6.2 Image Selection Matrix

	D1.1	D1.2	D1.3	D1.4	D1.5	D1.6	D1.7	D1.8	D1.9
D1.1									
D1.2									
D1.3									
D1.4									
D1.5									
D1.6									
D1.7									
D1.8									
D1.9									

Image Selection (Rating Design):

Image Selection (Version one): Two images from each set were chosen to be included within the sample for Study 2 (Chapter 8). The first repetition of images to be included was chosen using a simple 1-9 numbering system based on the image set order. The 2^{nd} repetition was done using a split number sample in which the number was chosen on the basis that there were at least 4-5 FD scores between each image. Given this the same numerical system was used, however the order began with set 5, ensuring that there was at least 4 FD points between the images chosen from the same sets. Images from each set are all similar structure but vary only in FD therefore to avoid preference affected by familiarity/structure rather than fractal dimension. At 4-5 points apart it is difficult to detect strong similarities between the images (see Table 6.3 for selection and difference information).

Table 6.3- Survey Type 1

	Image Set	FD 1st image	FD 2nd Image	Diff FD
A	Set01- 1116	1	6	5
B	Set02- 1135	2	7	5
C	Set03- 1161	3	8	5
D	Set04- 3003	4	9	5
E	Set05- 3056	5	1	4
F	Set06- 3077	6	2	4
G	Set07- 3091	7	3	4
H	Set08- 1043	8	4	4
I	Set09- 1048	9	5	4

Developing versions 2-4: In total 4 versions of the study was developed to ensure that preferences were a function of FD rather than the specific image sets used. Above outlines how version 1 was created, versions 2-4 was developed in a similar way however before image selection the Image Set order was randomised each time using a random number generator which output a unique random number generator order from 1-9 to arrange the stimulus sets. The same process of image selection was used on the second, third and fourth sample, ensuring again that images did not too closely resemble the images within the same set, leaving at least 4 points between them (table 6.4 demonstrates version 2 selections).

Table 6.4- Differences between FD measures

	Image Set	FD 1st image	FD 2nd image	Diff
H	Set08- 1043	1	6	5
G	Set07- 3091	2	7	5
F	Set06- 3077	3	8	5
A	Set01- 1116	4	9	5
B	Set02- 1135	5	1	4
C	Set03- 1161	6	2	4
I	Set09- 1048	7	3	4
E	Set05- 3056	8	4	4
D	Set04- 3003	9	5	4

Proposed Analyses:

Within the thesis there is a mix of SPSS and R analysis software used to explore the data. The rationale behind these choices are explored below.

Correlation & ANOVA in SPSS:

Correlation is used in this thesis to explore the relationship between the fractal dimension of the stimuli and the computational measurement of complexity (GIFratio). In addition Repeated Measures Analysis of Variance (ANOVA) was used to explore the mean scores for a selection of stimuli within study 3 in which participants were asked to rate on a scale (of 0-10) about how much they like the fractal images. Repeated measured ANOVA was also used to explore the differences amongst the frequency data based on the 2A-FC methods in studies 4, 5 & 6. The models used above have notable limitations because although variance is accounted their individual differences based on participants and stimulus are considered noise in this model. Serious problems have been identified with the use of ANOVA's in categorical variables, such as the forced-choice design and other categorical outcome variables (Jaeger, 2008). Despite the use of transformation, there are continued problems with using ANOVA's on categorical variable outcomes, justifying the use of mixed-effect models when using this type of data and offer advantages over using ANOVA.

Linear Mixed-Effect Modelling using R:

Although commonly used within linguistics, linear mixed-effect models (LMM) are a flexible and powerful tool for understanding and analyses response to the environment. LMM is a type of regression model that takes into account variables that would be considered of attributed as 'noise' in fixed-effects approaches. The model uses both fixed-effects such as the independent variables such as Age, Gender and stimulus as well as random-effects that are specific to the data sample, including individual variations in judgment and variances between stimulus used (as only a small selection of all possible stimulus that could be used). The analysis will be a logistic regression model with mixed effect as the dependent variable (fractal dimension image choice) is a binary variable. The model uses 3 different models exploring the classifications of the fractal images outlined above.

6.3.3. Connectedness to Nature Scale

The Connectedness to Nature Scale (CNS) was developed to measure individual differences in how emotionally connected to the natural world one feels (Mayer & McPherson-Frantz, 2004). The scale was developed by environmental psychologists hoping to find a reliable and stable measure to classify how much an individual identifies with the natural world around them, and any behaviour as a result of this connection. Mayer & McPherson-Frantz (2004) found that an individuals CNS score can be a significant predictor of subjective well-being and ecological behaviour and it has been confirmed as a reliable and easy to use measure of an individual's connection with the natural world. This measure was selected over other potential measures included the Nature Relatedness measure (Nisbet, Zelenski, & Murphy, 2009), The 'Inclusion of Nature in Self Scale (Schultz, 2002) or the Implicit Associates test-Nature (Greenwald, McGhee & Schwartz, 1998) because of the simplicity in wording (given it will be distributed to a sample whose first language was not English), the small number of statements to which to response (14 in total) and comprehensive cover of both cognitive and emotive responses to the natural world. Some example questions included within the measure are given below:

Question 2. I think of the natural world as a community to which I belong

1- Strongly disagree
2- Disagree
3- Neutral
4- Agree
5- Strongly agree

Question 8. I have a deep understanding of how my actions affect the natural world.

1- Strongly disagree
2- Disagree
3- Neutral
4- Agree
5- Strongly agree

Question 14. My personal welfare is independent of the welfare of the natural world. ***Reverse scored**

1- Strongly disagree
2- Disagree
3- Neutral
4- Agree
5- Strongly agree

Figure 6.6- examples from Connectedness-to-Nature Scale (Mayer & Frantz, 2004)

7.0 - Fractal Dimensions and Visual Complexity: An interrelated concept?

This thesis explores fractal dimension and suggest it as a new and specific form of natural complexity. The following study measures the fractal stimulus used throughout the thesis, generated to control for fractal dimension, and how they relate to the established computational complexity measure GIF ratio. Computational measures of complexity (such a GIF and Jpeg) have been found to offer reliable and unbiased measures of complexity over human judgments, which are open to bias from familiarity or experience. Gif ratio as opposed to purely fractal tools measures the image in terms of content of the scene and as such accounts for both fractal and non-fractal content. The study compares the FD scores from the generated images from a total of 81 images, with GIF compression scores. The results show highly significant negative correlations between fractal dimensions and the GIF ratio ($r=-.927$, $p<0.001$). The findings confirm that fractal dimension is significantly related to visual complexity. This result mean that it can be confidently proposed within this thesis that fractal dimension can be used to offer insight to aesthetic responses to fractal dimension and perceived visual complexity.

7.1 Background & Rationale:

Visual complexity is a difficult area to define; current attempts for a standardised definition are often inconclusive and face issues as a result of differing opinion as to whether complexity is an objective and subjective quality of a scene or image. This study adopts a method of complexity analysis to quantify the complexity of the stimulus. The GIF ratio, an established method of analysis (Forsythe et al, 2008) has been used and this will be compared to the Fractal Dimension of the images used within the analysis.

Previously human judgments have been used to assess the complexity of stimulus however evidence has subsequently demonstrated that human judgments of complexity are biased, based on level of familiarity and learning with the stimulus (Forsythe et al, 2008). The understanding of bias in judgment resulted in a search for new ways to quantify visual complexity without the need for human judgment scores. Forsythe et al., (2008) proposed that image processing techniques could be used as alternatives to human judgments and in a series of studies tested 4 image measurement techniques (Perimeter, Canny, JPEG & GIF) against previously established human judgment norms. Findings demonstrate that complexity could be reasonably approximated through a compression metric (Forsythe et al., 2008), however differences were found between the different types of compression techniques used with GIF showing strongest correlations with human judgments than other methods such as JPEG.

Whilst human judgments of complexity and compression methods are reported as correlated, further studies explored the relationship between complexity compression measures and aesthetics response. Forsythe et al., (2011) showed participants photos depicting real-life scenes (both natural and man-made) as well as abstract and figural art from established and renowned painters, all stimulus had been analysed for fractal dimension (FD) and visual complexity (GIF). The results show that preferences for photographs for natural scenes did not support the mid-range hypothesis of fractal preference (in which highest preferences are shown for images within the 1.3-1.5D range) and instead findings suggest higher complexity and fractal dimensions was positively correlated with preference for natural scenes. Abstract art however was found to be least preferred and containing the lowest FD and GIF scores. These findings suggested a linear relationship opposed to previous findings of an inverted-U relationship between complexity and aesthetic judgement (Berlyne, 1970; 1971, Taylor et al, 2001). As Art and photographs were used, this meant that a full range of fractal dimension was not covered as most images rose above the suggested mid-range peak of preference (D1.3-1.5), therefore it is important to explore this effect in a more controlled way to investigate the linear/mid-range relationship between fractal dimension and preference.

This thesis attempts to address this issue by using a set of computer generated stimulus which were developed to cover a full range of fractal dimension, and to enable the study to test the reliability of GIF and FD measures the study will analyse the stimulus within the current study. It is hypothesised that the Fractal Dimension of the stimulus will be significantly related to the compression complexity ratio (GIF).

7.2 Methodology

Stimulus:

Nine sets of fractal images were generated by Prof R Taylor & colleagues at University of Oregon, USA (See Figure 7.1 below for example of 1 set). These images were developed using a mid-point displacement technique. Using this technique allows prior 'setting' of FD measures to be out-put therefore allowing the same images to be manipulated to have the same foundation, but vary only in FD score. This technique allows more in depth analysis of fractal preference than many previous studies as it allows testing with a full range of Fractal Dimension values. Previous studies are limited with their stimulus sample and allows for only low, mid and high without a full range of FD values.

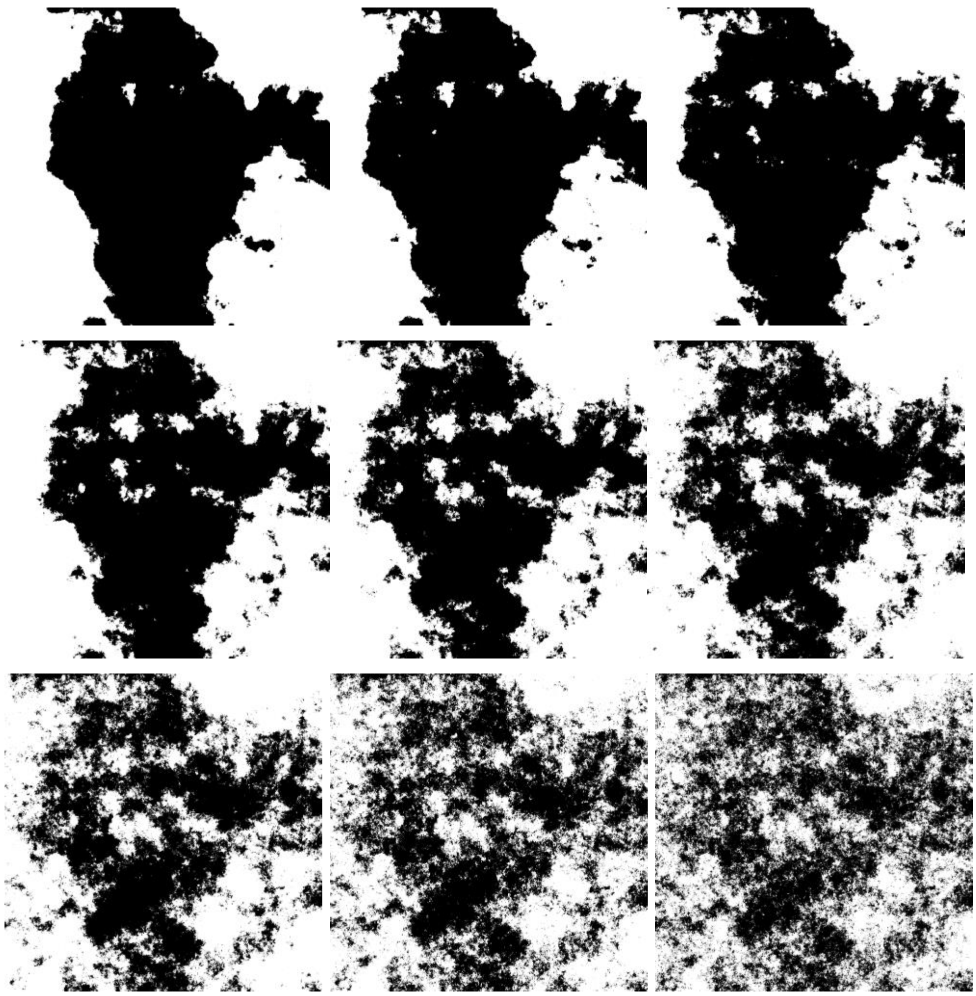


Figure-7.1- Example sample set of a full fractal range

Human complexity judgments are significantly influence by individual familiarity (Forysthe et al., 2008). This demonstrates inefficiencies in using human judgments to assess visual complexity, therefore methods of quantifying the complexity of images have been explored using the relationship between computational compression techniques and human judgments of complexity with success (Forsythe et al, 2008). All compression algorithms attempts to re-code the information within the stimulus to a smaller and compact representation and take 2 forms, lossless algorithms that code all information within an image to the smallest possible and lossy algorithms that compression the image further by removing details classified as too small for human judgments to notice.

GIF Ratio compression:

The GIF compression ratio is a lossless algorithm and as a method is best suited to sharp-edged and Black and White colour images. GIF compression retains the sharpness of information, particularly important to this current data set as the sharpness of edges defines the fractal dimension of the shape, therefore this method of comparison was chosen over others including JPEG which is better equip at compressing real world images. To measure the GIF compression ratio analysis requires original .BMP stimuli format, and this is compressed to GIF file. The amount of information between the original .BMP file and new compressed file are compared which gives the GIF Ratio score. Higher GIF ratio represent lower complexity images as they were compressed significantly from the original .BMP file. Higher GIF ratio scores are a result of less difference between the .BMP size and the GIF compression size. Each image within the set was analysed using this method and scores were compared to the Fractal Dimension outlined during stimulus development.

It is hypothesised that scores will be negatively correlated, as the fractal dimension increases the GIF ratio decreases.

7.3 Results:

The analysis found strong negative correlations between FD of visual stimulus and GIF complexity measures. Results found a strong significant correlation between the fractal dimensions measures of the stimulus and the GIF ratio complexity measure (r(79)=-.93, p<0.01). This strength of the correlation demonstrates that fractal dimension and complexity are related constructs (See Figure 7.2); therefore the results found in the study can be confidently applied to perceptual responses to complex as well as fractal images.

Table 7.1- FD Stimulus and GIF ratio correlation

	Stimulus FD
GIF ratio	-0.927
Sig. (2-tailed)	.001

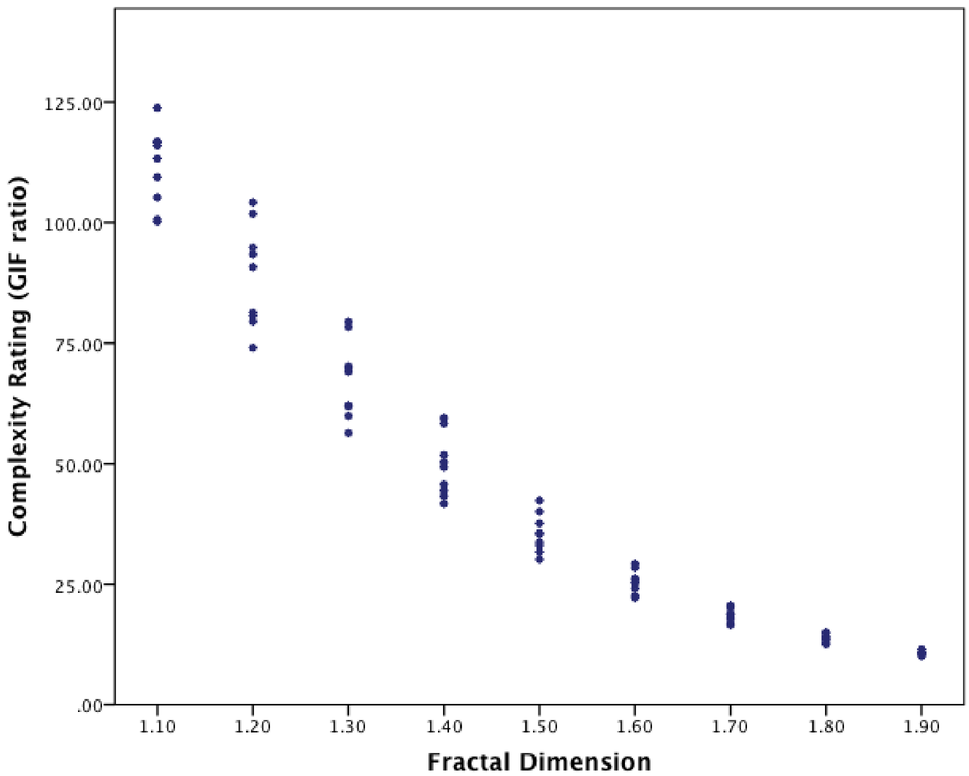


Figure-7.2- Correlation between Fractal Stimulus and GIF compression score

7.4 Discussions:

The results suggest a very strong relationship between fractal dimension of the stimulus and computation visual complexity compression measures (GIF). High correlation between FD measures and GIF scores support the findings of Forsythe et al., (2011) who found significant correlations between fractal dimension (measured using box-count technique) and visual complexity (measured using GIF compression technique), and additional correlations between these scores and aesthetic judgments. The findings of the current study support these high correlations and confirm a strong relationship between fractal dimension and visual complexity.

On the basis of these findings, the results of the thesis using this controlled fractal stimulus can also offer insights into visual complexity. To explore the aesthetic response to the complex/fractal stimulus, participant's responses will be explored for frequency of choice across the fractal scale and modelled in 2 main ways. Firstly exploring the probability and predicting variables associated with participants preferring the mid-range over images not within the mid-range and secondly, the probability and predicting variables associated with participants preferring the more complex over simple images. Further studies will attempt to explore the aesthetic impact of the stimulus and investigate to potential individual differences that could shape aesthetic choices. Further implications of the findings will be explored in relation to literature within Chapter 13.

8.0 Cross-cultural comparisons UK and Egypt
(A Ratings Scale Design)

Aesthetic relationships with complex images have been the subject of much investigation. Fractal patterns offer an up to date, stringent quantitative measurement of complexity in a visual pattern. Fractal patterns have also been found to contribute to our experiences of beauty and display aesthetic responses akin with Berlyne's (1970; 1971) inverted-U hypothesis. Participants were 354 undergraduate participants based in University of Liverpool and Salford Universities (UK) and Menoufia University (Egypt). They were asked to rate beauty of 27 fractal images on a scale of 1-10.. The results found that overall the peak preference occurs lower than previously considered (D1.2) opposed to D1.3-1.5. Further analysis finds differences between the groups in patterns of preference. The UK sample demonstrated a slight inverted-U shaped curve, however the Egyptian sample show a negative linear relationship, the lowest FD images receiving the high scores and incrementally lower scores were given for higher FD patterns. Results also show significant differences between Genders. These findings raise questions about the cross-cultural validity of previous findings for aesthetic response to fractal patterns. They suggests tentatively that environment, even large macro environments (such as country) influence our aesthetic response, leading the researchers to question the potential impact of small micro-environments on aesthetic responses.

8.1 Background/Rationale:

Visual complexity has been on interest to those studying aesthetic experience since the early foundation of the field of Empirical Aesthetics.. Measuring the scale of order and complexity in a scene has been approached from multiple angles (see Chapter 1 & 2) despite the long term interest defining and measuring complexity is still a difficult and unresolved area. Fractal geometry has been suggested as a new way to quantify the complexities found in nature (See chapter 3 for full review). Patterns of preference for complexity have been found to take a variety of forms; some finding that complexity of an image is positively related with positive aesthetic responses (Forsythe et al, 2011) or that peak preferences lie at the mid-point of complexity (Berlyne, 1970). A number of studies have found that the inverted-U shaped function of preference to reflect aesthetic responses to fractal patterns (Taylor et al, 2001; Spehar et al, 2003). Results suggest that complexity and fractal dimension may be an interrelated construct, with previous studies within this thesis supporting this assertion (Chapter 7).

The current study was based upon a replication of a piece of cross-cultural research conducted by Souief & Eysenck (1971) exploring the differences in preference across UK and Egyptian participants towards complex patterns. Souief & Eysenck's results suggest unusual differences across cultures in terms of preference for visual complexity. As Fractal images are a relatively new method of measurement for complexity, it was decided that the study be replicated to examine the stability of Souief & Eysenck's original findings and to examine the impact of fractal dimension of preferences as a new measure of complexity in the visual environment. The complexity examined is based on natural complexity, rather than any other descriptions, (definitions and measurement of complexity is discussed previous chapters). This allows us to consider if the impact of environmental/natural complexity on preference. Is it something about the environment in which we spend time that contributes to our preferences for complex natural shapes?

The study aims to explore the impact of culture, gender and age on a group of non art-trained individuals to assessing the aesthetic quality of fractal complexity. The study intends to add additional evidence to Souief & Eysenck's (1971) non-art trained sample to explore if a similar relationship to Birkhoff (1932) shapes visual complexity exists to fractal complexity.

8.2 Methodology

Participants:

The participant pool was recruited from undergraduate students studying in the UK (N=154, Females=122 Mean Age=21.5, SD=4.82) and Egypt (N=200, Females=100 Mean Age=19.5, SD=1.16). Participants studied a variety of subjects, all participants with the exception of 2 studied science based disciplines. On this point the results gathered can be compared to Souief & Eysenck's (1971) non art-trained participants recruited in their sample.

Design:

An independent samples design was used. Participants were randomly assigned to 1 of 4 versions with the randomisation coming from distribution of the questionnaires. In all versions participants were asked to rate a selection of 27 fractal images, each version containing equal numbers of patterns varying from the lowest to the highest FD patterns (see methodology in chapter 6 for full methodological explanation).

Materials:

Computer generated fractal patterns were used (for full details on development and specific image sampling details see chapter 6). Using abstract generated stimulus over real-life scenes allowed for control in developing a full range of fractal dimension combatting previous studies limitations with an available range of fractal patterns for full exploration along the entire fractal dimension scale (see Figure 8.1 below for example).

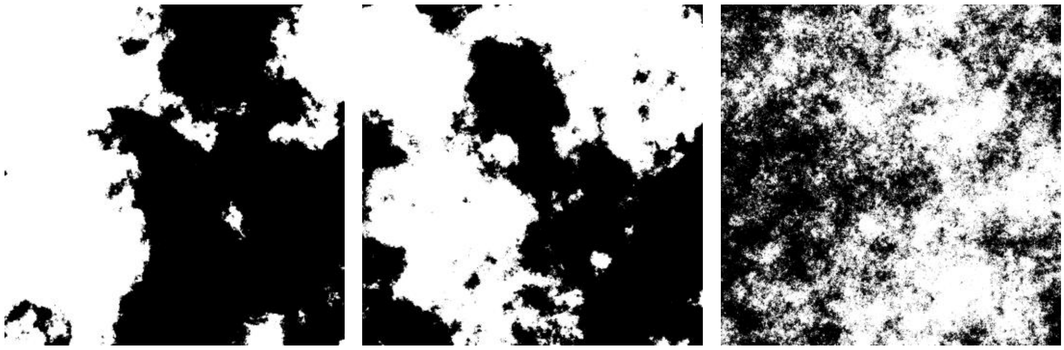


Figure 8.1- Example of Low (1.2), Mid (1.4) and High (1.9) Fractal patterns.

Procedure:

Participants were recruited using opportunity samples within each university. The task was distributed using hardcopies of questionnaires that asked participants to rate (on a scale of 0-10) how beautiful they found the image. Four versions of the questionnaire were developed which included 27 separate fractal images from the set chosen in a quasi-random method (see chapter 6 for full details). Participants were also asked to provide details including age, gender and course of study.

Analysis:

A series of analyses were conducted to explore the overall patterns of the preference data across the FD scale. Fractal Dimension was also grouped into the categories Low, Mid & High to allow analysis of direction of preference positive or negative along the FD scale. Additional analyses were conducted to explore the impact of Country, Age and Gender on aesthetic values of fractal patterns.

8.3 Results:

A series of analyses were conducted to explore the data set as a whole, to examine the mid-range hypothesis, as well as explore the sub-cultural differences between Cultures, and the individual differences of Age and Gender. Both the full range and the modified compressed groupings (Low-Mid-High) have been used in the analysis to allow comparisons to previous studies to be made.

Overall trends in the Data Set:

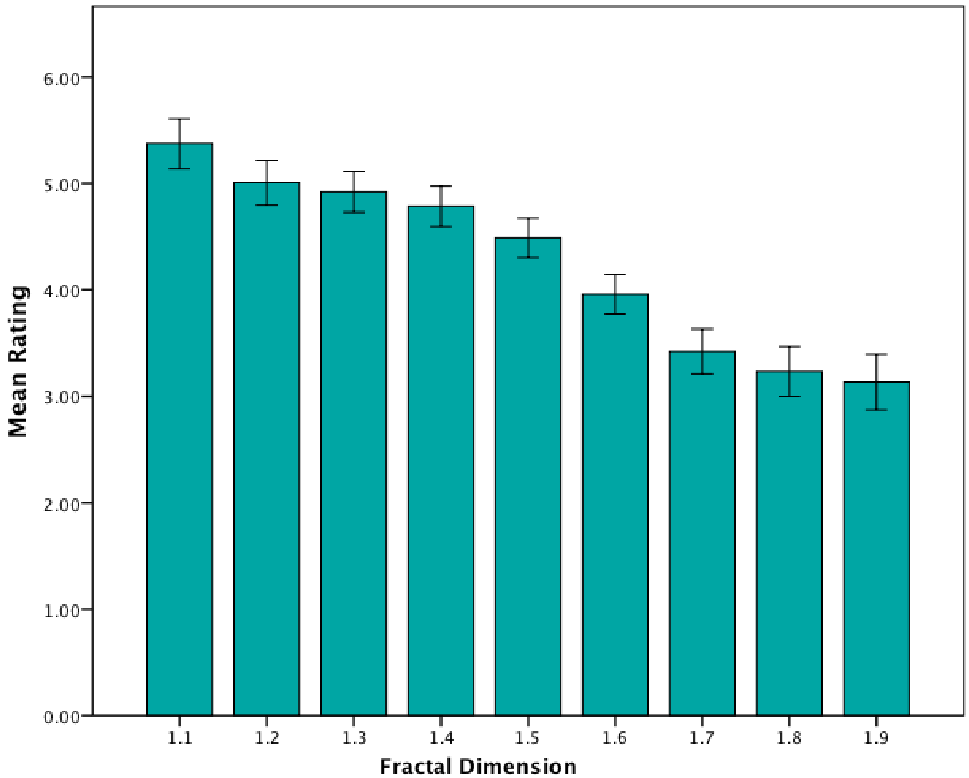


Figure 8.2 :Mean scores in preference for fractal scale.

As demonstrated in Figure 8.2, the overall trend of the data suggests that differences exist between the levels of fractal dimension. The results show the highest preferences for lowest fractal dimension D1.1 (M=5.37 SD=2.24) with a gradual decrease of rating throughout the mid range D1.4 (M=4.78, SD=1.81) and reaching it's lowest rating at the high point the fractal scale D1.9 (M=3.13, SD=2.49). Mauchly's test indicated that the assumption of sphericity had been violated, $\chi2(35) = 1164.31$, $p = .0001$, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .390$). The results show that there was a significant effect of fractal dimension, $F(3.12, 1102.66) = 72.92$, p =

.0001, η2*p*=0.171. These results suggest that preference ratings differ significantly between each fractal dimension.

Post hoc pairwise comparisons were performed across the 9 different fractal dimensions to explore the point(s) at which these significant differences can be seen. Analysis found significant differences of preference ratings between nearly all of the different levels of fractal dimension. Table 8.1 demonstrates the significant and non-significant relationships between each level, with the significant difference in orange and the non-significant differences in white. There results show clusters of similar (non-significantly different) groups within the data. The results suggest clusters in which preference is most variant (evidence in groups of white). The overall analysis demonstrates that preference differences significantly as a function of fractal dimension and that higher preference are grouped towards stimulus at the lower end of the fractal dimension scale, rather than the mid or higher point.

Table 8.1- Image post-hoc significant differences matrix

	D1.1	D1.2	D1.3	D1.4	D1.5	D1.6	D1.7	D1.8	D1.9
D1.1		.367*	.453*	.588*	.886*	1.415*	1.953*	2.141*	2.242*
D1.2			.086	.220	.518*	1.048*	1.586*	1.774*	1.874*
D1.3				.134	.432*	.962*	1.500*	1.688*	1.788*
D1.4					.298	.828*	1.366*	1.554*	1.654*
D1.5						.530*	1.068*	1.256*	1.356*
D1.6							.538*	.726*	.826*
D1.7								.188	.288
D1.8									.100
D1.9									

* The mean difference is significant at the Adjustment for multiple comparisons: Bonferroni.

Groupings of results (Low - Mid - High):

To explore the direction of preference demonstrated in the initial analysis, the data was grouped into 3 categories Low, Mid and High allowing further comparisons to be made between the preference scores as well as examine the stability of the mid-range hypothesis previously proposed. Figure 8.3 demonstrates that preferences for fractal patterns is a structured as a negative linear relationship with the highest rated images falling at the lowest end of the fractal scale.

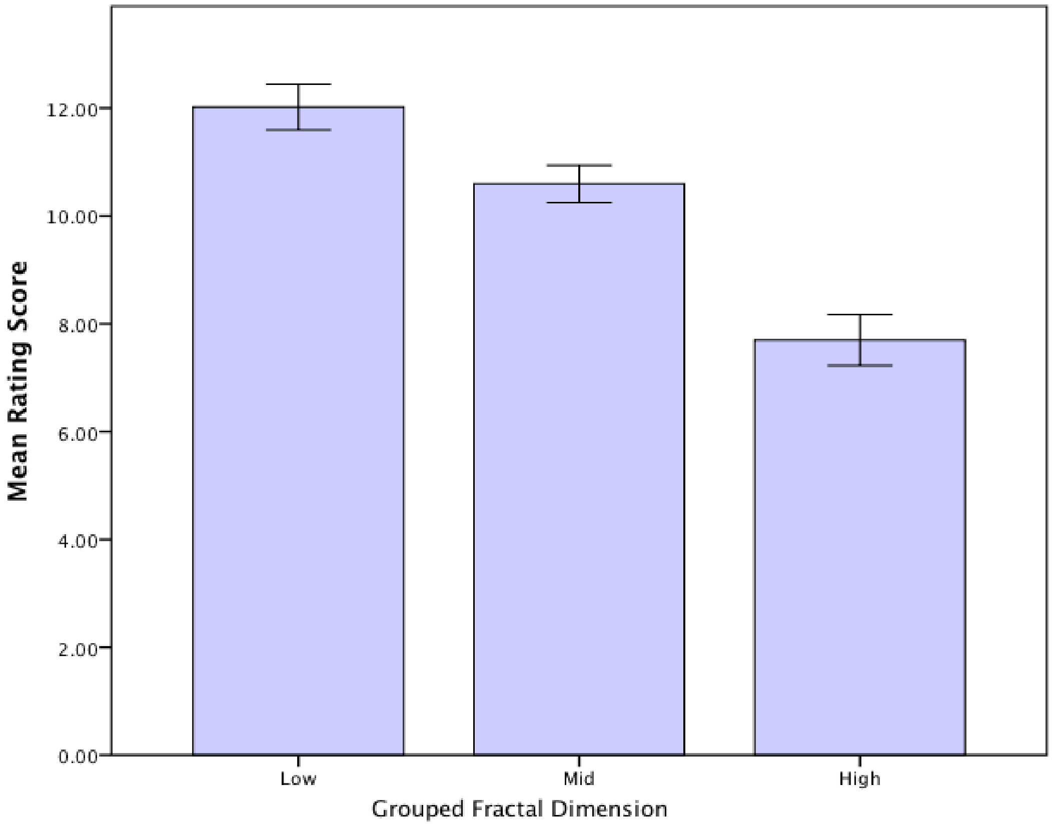


Figure 8.3: Mean scores in preference for categorised fractal scale.

Examining the means across the 3 levels with the highest scores for 'Low' (M=5.19, SD=2.13), the Mid grouping scoring significantly lower on average (M=4.73, SD=1.81) and the High group receiving the lowest beauty rating scores (M=3.44, SD=2.17). Mauchly's test indicated that the assumption of sphericity had been violated, $\chi2$ (2) = 225.985, p = .0001, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ε = .679). The results show that there was a significant effect of fractal dimension on preference ratings, F (1.357, 479.046) = 114.123, p = .0001, $\eta 2p$=0.244. These results suggest that preference ratings differ significantly between each fractal dimension. Post hoc pairwise comparisons demonstrated in Table 8.2, were performed across the 3 different fractal levels to explore the point(s) at which these significant differences can be seen. Analysis shows that each level differs significantly from each other.

Table 8.2- Post-hoc Pairwise Comparison matrix

	Low	Mid	High
Low		**1.426***	**4.323***
Mid			**2.897***
High			

* The mean difference is significant at the Adjustment for multiple comparisons: Bonferroni.

Egyptian patterns of Fractal Preference:

To explore the patterns of preference across culture, each culture was explored separately initially. Looking at the Egyptian sample, a repeated measure ANOVA was conducted to examine the effect of fractal dimension on preference patterns.

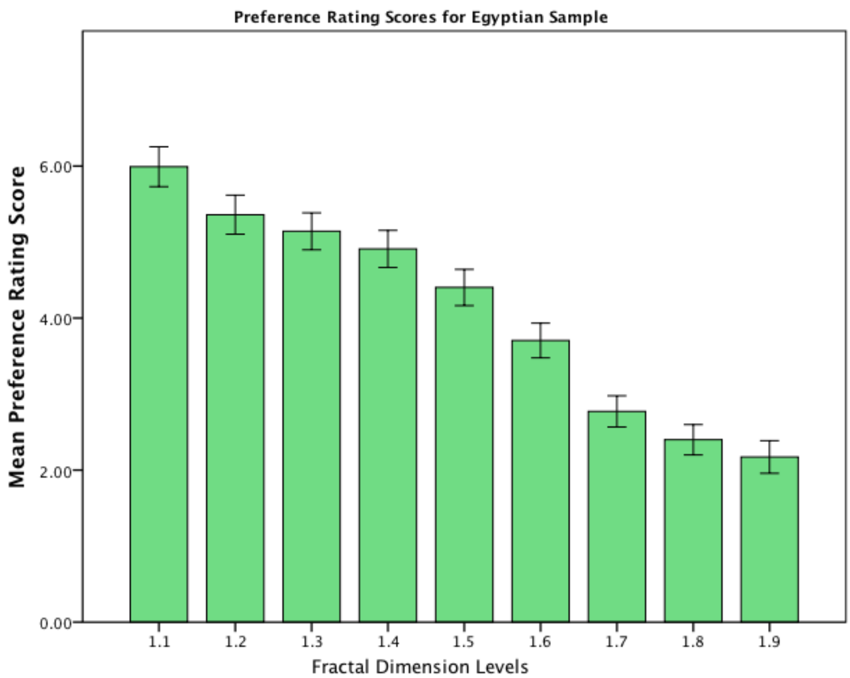


Figure 8.4 Graph of Choice Frequencies across the fractal scale.

The Egyptian sample as evidence in Figure 8.4 demonstrates the highest preference scores for fractal patterns at the lowest point D1.1 (M=5.99, SD=1.88) with scores dropping incrementally with FD, with the lowest preference scores are seen for to the most highly complex/fractal patterns of D1.9 (M=2.17, SD=1.54). Mauchly's test indicated that the assumption of sphericity had been violated, $\chi 2$ (35) = 132.62, p = .0001, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ε = .856). The results show that there was a significant effect of fractal dimension, F (6.848, 1362.706) = 159.77, p = .0001, $\eta 2p$=0.445. These results suggest that preference ratings differ significantly between each fractal dimension for the Egyptian sample. Post hoc pairwise comparisons were performed across the 9 different fractal levels to explore the point(s) at which these significant differences can be seen. As can be seen in Table 8.3 below, level differs significantly from each other for the most part, however some groupings of similar preferences (non-significant) FD values can be seen and suggest that at points distinctions between each FD level are not significantly related to preference.

Table 8.3: Table of post-hoc pairwise comparisons for Egypt Sample.

	D1.1	D1.2	D1.3	D1.4	D1.5	D1.6	D1.7	D1.8	D1.9
D1.1		**.632***	**.850***	**1.082***	**1.590***	**2.287***	**3.220***	**3.593***	**3.820***
D1.2			**.218**	**.450**	**.958***	**1.655***	**2.588***	**2.960***	**3.188***
D1.3				**.232**	**.740***	**1.438***	**2.370***	**2.743***	**2.970***
D1.4					**.508***	**1.205***	**2.138***	**2.510***	**2.738***
D1.5						**.697***	**1.630***	**2.003***	**2.230***
D1.6							**.933***	**1.305***	**1.533***
D1.7								**.373**	**.600***
D1.8									**.228**
D1.9									

* The mean difference is significant at the Adjustment for multiple comparisons: Bonferroni.

UK patterns of Fractal Preference:

To explore the patterns of preference across culture, each culture was explored separately initially. Looking at the UK sample, repeated-measures ANOVA was conducted to examine the effect of fractal dimension on preference patterns.

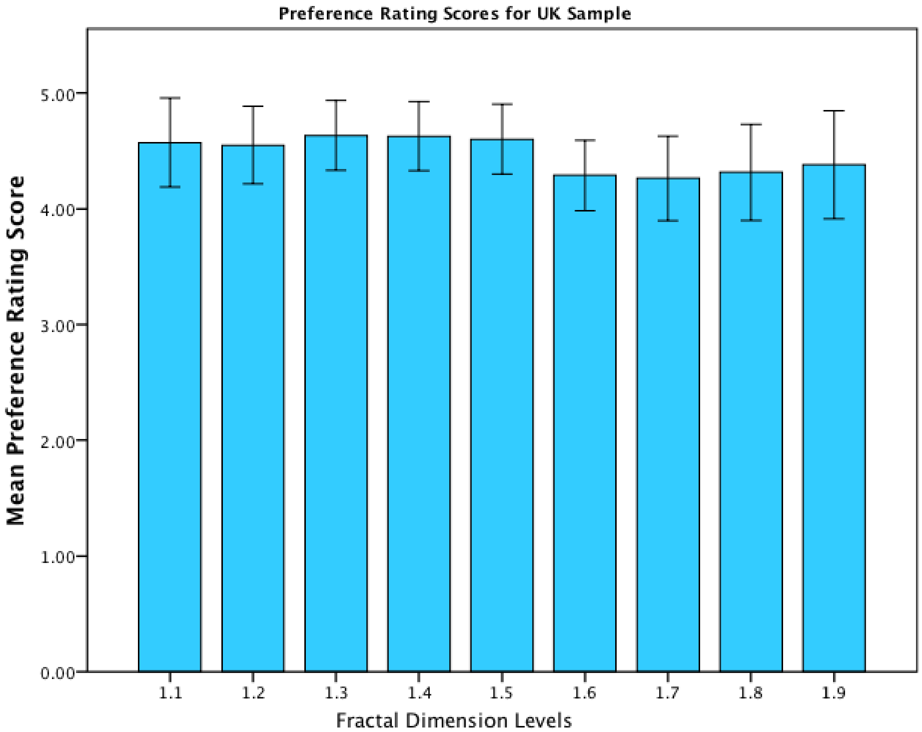


Figure 8.5 Bar Chart of Frequency of Choice across the fractal scale.

The UK sample as evident in Figure 8.5 shows little difference between the preferences ratings for each individual Fractal Dimension. The highest scores are seen 2 points, D1.3 (M=4.63, SD=1.89) and D1.4 (M=4.63, SD=1.87) with the lowest scores for D1.6 (M=4.29, SD= 1.91) and D1.7 (M=4.26, SD-2.29). There are no significant difference in preference ratings across the fractal scale in the UK sample (Mauchly's sphericity had been violated, $\chi 2$ (35) = 902.98, p = .0001, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ε = .262). The results show that there was a no significant effect of fractal dimension, F (2.069, 316.500) = 0.954, p = .389. These results suggest that preference ratings show no significant difference between each fractal dimension for the UK sample. As such no further post hoc pairwise comparisons were performed.

Multivariate ANOVA's:

A series of multivariate analysis of variance attempted to explore the influence of Cultural Group (UK or Egypt), Gender (Male or Female) and Age on the mean scores of low, mid and high fractal image choice. These analyses aim to unpick if individual differences in participants are significantly influencing preference scores awarded.

Cross-cultural analysis:

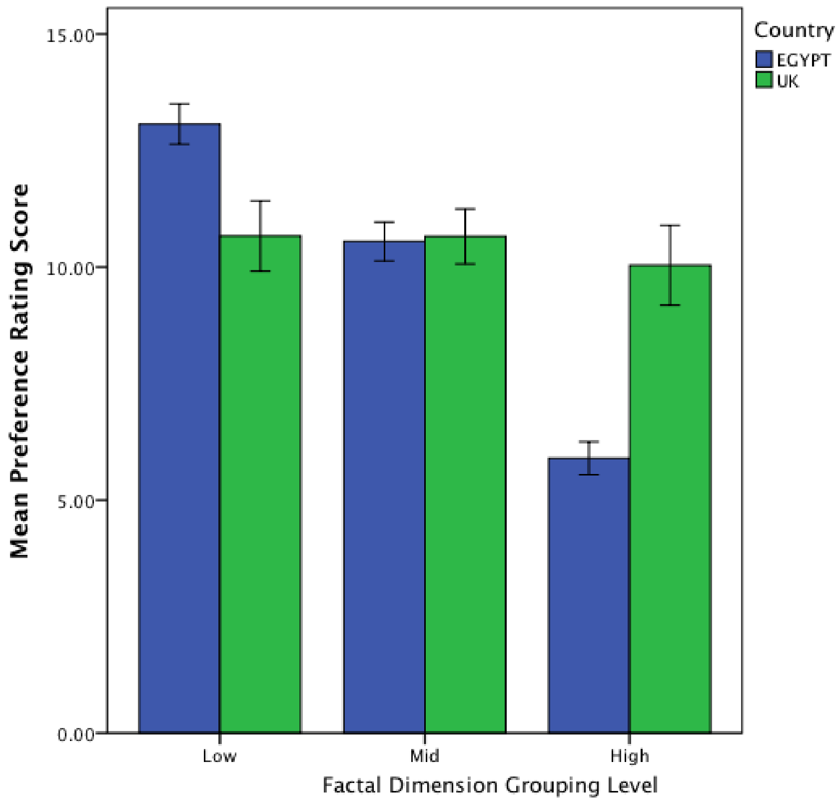


Figure 8.6 Bar chart of Mean Preference Scores between the 3 levels across Culture

Figure 8.6 demonstrates the variety in preference scores awarded across the 3 groupings between cultures, there is a marked negative linear preference relationship in the Egyptian Sample with the UK sample showing much more consistency in preference across the FD groupings (See Table 8.4 for mean summaries). The Egyptian sample has significantly higher mean rating scores for the lower FD grouping (Mean=13.07, SD=3.09) than the UK Sample (Mean=10.66, SD=4.73) where as the UK group show higher mean preference rating for the high FD group (Mean=10.08, SD=5.38) than the Egyptian Sample (Mean=5.89, SD=2.54).

Table 8.4: Grouped FD Mean scores in preference between UK and Egypt.

	UK (N=154)		Egypt (N=200)	
	Mean	**SD**	**Mean**	**SD**
LowFDMean	10.66	4.73	13.07	3.09
MidFDMean	10.66	3.71	10.55	2.98
HighFDMean	10.04	5.38	5.89	2.54

Multivariate ANOVA demonstrates that there is a significant main effect of culture. Mauchly's test indicated that the assumption of sphericity had been violated, $\chi 2$ (2 = 171.04, p <0.001, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ε = .722). The results show that there was a significant main effect of fractal level, F (1.443,508.04) = 110.997, p < .001, $\eta 2p$=0.240 and a significant interaction between fractal level and ethnic group F (1.443,508.04) = 76.434 p < .001, $\eta 2p$=0.178. Pairwise comparisons were performed across the 3 different fractal levels to explore the point(s) at which these significant differences can be seen. As can be seen in Table 8.5 below, each level differs significantly from each other at each.

Table 8.5 Post-hoc pairwise comparisons across Country

	Low	Mid	High
Low		**1.263***	**3.898***
Mid			**2.635***
High			

* The mean difference is significant at the Adjustment for multiple comparisons: Bonferroni.

Cross-gender analysis:

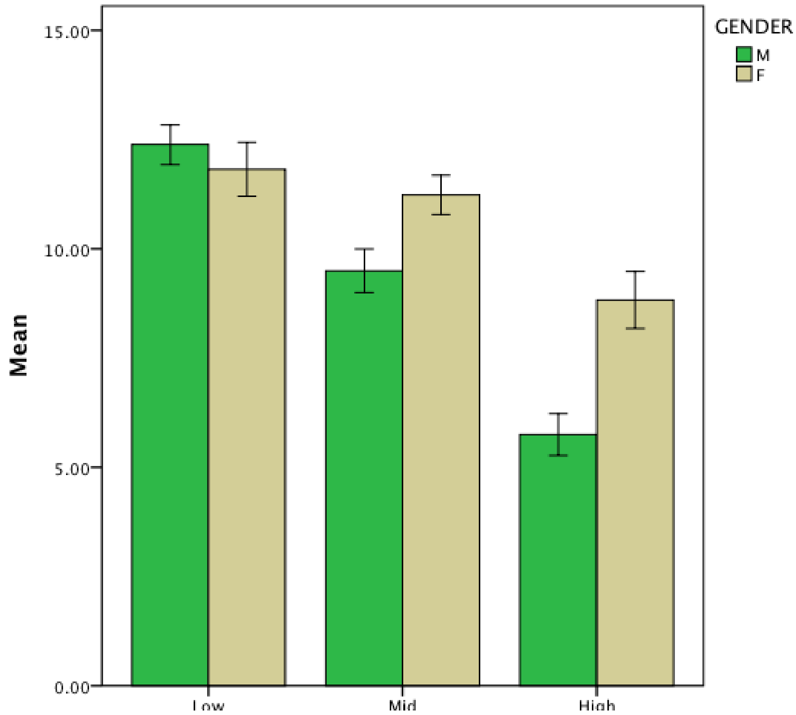


Figure 8.7 Bar chart of Mean Preference Scores between the 3 levels across Gender

As demonstrated in Figure 8.7, Males appear to show a negative relationship of preference across the FD groupings with Females showing a similar but less marked difference across the three groupings. Detailed in Table 8.6, the means differ significantly between gender across the MidFD and HighFD groups but not the LowFD group suggesting more consistency in preference for lower FD values than Mid or High.

Table 8.6: Grouped FD Mean scores in preference between Males and Females

	Males (N=121)		Females (N=222)	
	Mean	**SD**	**Mean**	**SD**
LowFDMean	12.384	2.54	11.82	4.65
MidFDMean	9.49	2.75	11.23	3.39
HighFDMean	5.75	2.64	8.83	4.51

Exploring analytically the means outlined in Table 8.6, Mauchly's test indicated that the assumption of sphericity had been violated, $\chi 2$ (2) = 209.64, p <0.001, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ε = .685). The results show that there was a significant main effect of fractal level, F (1.37, 467.6) = 130.27, p < .001, η2*p*=0.276 and a significant interaction between fractal level and Gender group F (1.37, 467.06) = 18.62 p < .001, η2*p*=0.052.

Cross-Age Analysis:

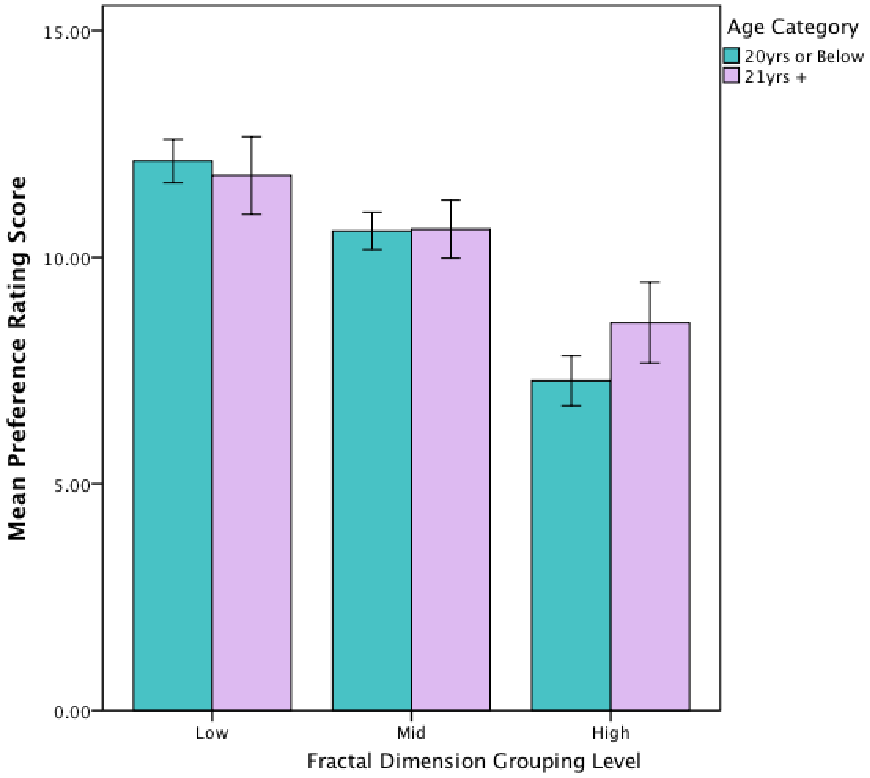


Figure 8.8 Bar chart of Mean Preference Scores between the 3 levels across Age Category

As demonstrated in Figure 8.8, a negative linear relationship for both the groups within the 20 & under and Over 20 age groups. Exploring analytically the means outlined in Table 8.7, Mauchly’s test indicated that the assumption of sphericity had been violated, χ2 (2) = 223.155, p <0.001, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ε = .680). The results show that there was a significant main effect of fractal level, F (1.36, 478.76) = 188.57, p < .001, η2*p*=0.201 and a significant interaction between Fractal Level and Age Group F (1.37,478.76) = 3.66, p < .05, η2*p*=0.01.

Table 8.7: Grouped FD Mean scores in preference between Age groupings.

	20 & Under (N=238)		21 & Over (N=116)	
	Mean	**SD**	**Mean**	**SD**
LowFDMean	12.13	3.75	11.81	4.67
MidFDMean	10.58	3.23	10.62	3.49
HighFDMean	7.28	4.30	8.56	4.52

Additional analysis found that there are no significant 3 ways interactions between Culture, Age Group and Gender for any of the 3 FD groupings (Low p=-.63, Mid p=0.92, High p=0.54).

8.4 Discussion:

The results of this initial study support the findings of Souief & Eysenck (1971) in terms of patterns of preference in complexity for non-art trained individuals and cross-cultural differences. The findings of the study raise important questions about the role that individual differences play in preferences for fractal patterns. The findings demonstrate that Gender as well as Cultural Environment (UK/Egypt) should be considered when exploring aesthetic responses to fractal patterns as they show significant differences in patterns of preference.

Patterns of Preference:

The study found no statistical support for the mid-range hypothesis proposed by Taylor et al., (2001). Instead preferences seem to be displaying a linear pattern of preference, with the overall patterns showing peak preferences at D1.1 with incremental falls in preference from this point. This finding offers conflicting results to many of the current findings including the mid-range preference hypothesis (Taylor et al., 2001) as well as Berlyne's (1970) inverted-U function of complexity preference. Results are more aligned with Forsythe et al's., (2010) study that found linear preference for complexity and fractal dimension, however the direction of the linear preference is negative rather than positive. Forsythe et al., (2008) found that as complexity scores and fractal dimension increased (particularly for natural images/photographs), as did preference scores, however the opposite is found with the current sample. Most prominently this negative relationship of FD and preference is seen within the Egyptian sample, suggested cultural factors may play a role in developing the direction of complexity/fractal preference.

Cross-cultural findings:

The current findings show differences in patterns for fractal preference based on culture. Whilst the UK sample demonstrates statistically stable scores of preferences for all ranges of fractal images, the Egyptian population demonstrates a linear pattern with the lowest FD and most simple images the most highly preferred and preference falling from this point. This study aimed to replicate some aspects of Souief & Eysenck's (1971) study. With the use of fractal patterns over Birkhoff's (1932) polygons the impact of a specific type of complexity, fractal complexity, we can explore in a more controlled way, how complexity preference differs between cultures. Whilst Souief & Eysenck (1971) used both art-educated and non-art educated students this study used a sample of participants came from a non-arts education background (with the exception of 2, studying Architecture and Media). Results found higher preferences for the lower fractal dimension/complexity patterns in the Egyptian sample and higher preference for the higher complexity group from the UK sample. This result support Souief & Eysenck's (1971) finding that UK non-art trained sample demonstrated higher preference for complex images and Egyptian non-art training sample demonstrated higher preference for the simple images. This result suggest that fractal dimension is a robust measure of visual complexity and preference behave between cultures follows the same pattern as seen when using other stimuli controlled for complexity.

Although the differences have been found between cultures, there are limitations in terms of the classification of culture as a predictor of preference. It could be proposed that the environment in which we spend time and are exposed shapes our preferences, this is supported by the mere exposure hypothesis (Zajonc, 1968) and more recently the processing fluency hypothesis (Reber et al., 2004). Considering these theories from a cross-cultural perspective, the difference found between the countries could be a result of the differences in the visual environments in which people spend the most time. When making these judgments however, acknowledgement is needed for the variety of visual environments across culture. People can live in towns and urban industrialized areas or rural and natural areas, with visual environment varying significantly from location to location. The micro sub-environments (such as urban-rural distinctions) rather than the macro cross-cultural environments (exploring across countries) may offer greater insight into the role that daily visual experiences play on preference for complex and fractal patterns and should be explored fully understand how visual environment can influence preference for fractal and complex shapes.

Gender findings:

Results demonstrate some marked differences in gender. Differences in both the mid and high groups but not with the low group. Females showed higher preference for the higher FD patterns and lower preferences for the lower FD patterns, with male participants demonstrating the opposite relationship. No group differences were seen between scores of fractal patterns in the mid-range group. Previous findings have shown gender difference in processing of aesthetic stimuli (Cela-Conde et al., 2009). The hunter-gather hypothesis (Silverman & Eels., 1992) offers one theory to account for differences in perceptual strategies between males and females. Further findings suggest that males look at the whole picture during aesthetic judgment, where as females tend to pay attention to smaller details within the picture (Cela-Conde et al., 2009), this distinction in perceptual processes may account for the difference as the higher fractal/complex images include much more details and information that females may attend to more, whereas the lowest fractal images resemble a single-form figure or space that could be considered as a whole picture. These studies may offer some insight into the gender differences seen in preference for fractal/complex patterns in the current study although to make assumptions about the perceptual differences are tentative because of the nature of the study, it appears that there are marked aesthetic judgment differences between gender.

Age findings:

There was very little variation between the age groups in terms of preference for fractal patterns. Within previous literature, there is some evidence to suggest that age differences in preference for landscape/nature studies, suggesting that adolescents and elderly participants demonstrate preferences significantly different to other age populations such as children and mid-aged adults (Balling & Falk, 1982). The sample sizes used were not equal and range of ages limited with most participants (N=236) falling within the 18-20 category. To make assumptions about age and preference for fractal patterns we need a larger and more varied sample of ages included within the study which will be explored in future studies of this thesis.

Conclusions:

Overall the study appears to show that there are key individual and cultural differences in preference patterns for fractal complexity, and these findings support those of Souief & Eysenck (1971) regarding visual complexity and aesthetic judgment. It highlights the need for further exploration in the field of fractal complexity, particular unpicking the aspects of the environment that contribute to our preferences. Could mere exposure (Zajonc, 1968) result in changes with preferences? and if so are these highlighted in macro-cultural environments (such as Country) or within micro-cultural environments such as classifications of daily environments (as urban and rural for example)?
The study supports the link between fractal dimensions as an associated component of visual complexity and highlights the role that fractal dimension can play in explore the differences in aesthetic responses to natural-like images. Further studies are needed to unpick the tentative differences in preference responses across culture and gender and the following studies within this thesis attempt to go some way towards addressing this gap.

9.0 Validating the mid range hypothesis for fractal preference.

This study attempts to replicate the findings of Taylor et al (2011), which suggests a preference peak at the mid-range of fractal points. This mid-point peak mirrors Berlyne's (1963) inverted-U hypothesis demonstrating preference for optimal complexity and highlights a potential link between the two concepts, something previously suggested by Forsythe et al., (2006). The current study aims to re-test these findings across a wider and varied sample using a 2A-FC method with computer generated natural-looking fractal stimulus to control for potential bias found in previous studies. The sample was recruited using online recruitment tools including MTurk, meaning that the sample represented an international population. The study uses two analysis methods that demonstrate analytic progression. The first stage involved ANOVA and mapping of frequency of choice data to explore the overall patterns in the data, however because of the associated experimental issues using these design for binary and categorical data analysis, a linear mixed effect modelling was also conducted. LME was used to explore the data more thoroughly and will test three models to test the fit of the mid-range and complexity hypotheses as a significant predictor of preference. Results from all models demonstrated significant main and interaction effects between individual differences as predictor of fractal preference.

9.1 Background & Rationale:

Previous research points towards an optimal range of fractal preference within the fractal scale, showing links and support for Berlyne's (1970) arousal theory for complexity. While research has established the aesthetic appeal of images displaying fractal properties (Taylor, 1999), an optimal range emerged from the fractal spectrum that seemed to demonstrate higher preference. Taylor et al (2001) found that images within the mid-range D values (1.3-1.5) were consistently preferred regardless of how the fractal images were generated (Taylor et al 2001, Spehar et al 2003). This offered an interesting link between fractals and complexity, both of which seem to follow a similar preference pattern. Studies have suggested that people's preference is universally set at 1.3 because of continual visual exposure to nature's patterns (Aks & Sprott, 1996), supporting Zajonc (1968) mere exposure theory and more recently the processing fluency hypothesis (Reber et al, 2004) as many of natures processes display mid-range fractal properties. Others have suggested evolutionary foundations.

Complexity and Fractal Dimension from previous studies within this thesis are intertwined in aesthetic preference; Forsythe et al (2006) found both concepts to be predictors of preference. Both were found to be positively correlated with preference, suggesting a linear rather than mid-range preference for both concepts. Replication of Berlyne's arousal potential by Martindale et al., (1990) failed to replicate many of Berlyne's (1970) findings, including the inverted-U hypothesis. It seems that the patterns of preference toward complex and fractal stimulus appear to differ in preferential patterns and this study attempts to replicate the findings of Taylor et al., (2011) to support the mid-range theory of fractal preference.

Research Statement:

This study attempts to replicate findings suggesting preference is centred at the mid-point in fractal scaling, using computer generated stimulus. This was considered important given the variation in preference patterns in previous findings. The study uses a similar but adapted methodology to Taylor et al., (2001). The study aims to explore the impact of fractal dimension independently from the core structure of the images therefore a randomised pairing method different to Taylor et al's., (2001) original design of within group rating. The study also aims to explore the relationship between fractal patterns and complexity with the aim to investigate Berlyne's, and Taylor's mid-range preference hypothesis. Previous studies within this thesis have found additional support for linear relationships with preference across culture (See chapter 8), to test this further, this study uses linear mixed-effects modelling to explore if the linear complexity or the mid-range hypothesis is a better model with which to map preference for fractal patterns.

9.2 Methods:

Participants:

Participants were recruited via MTurk and additional web based distribution services. MTurk is digital platform in association with Amazon.com. Participants register online to be notified for recruitment calls, this method allow access to a sizable and willing participant pool. MTurk recruits participants from a range of ages and socioeconomic backgrounds from around the world. The variety of participants allows for data collection with higher external validity.

In total data was collected from 291 participants, whose ages ranged from 18 to 74 with a mean age 29 (SD=9.6). Of the sample 61.5% (N=179) were male and 38.5% (N=112) were female. Participants were recruited from all around the world, in total 31 countries made up the sample. Table 9.1 below provides a full list of the countries included in the sample and the size of the participants from each country.

Table 9.1 - Country N and total % of sample

Country	N	Total %	Country	N	Total %
Argentina	2	0.7	**Jamaica**	1	0.3
Austria	3	1	**Japan**	1	0.3
Brazil	1	0.3	**Korea, R**	1	0.3
Bulgaria	1	0.3	**Macedonia**	3	1
Canada	7	2.4	**Mexico**	1	0.3
China	10	3.4	**Pakistan**	3	1
Croatia	2	0.7	**Philippines**	2	0.7
Denmark	1	0.3	**Poland**	1	0.3
Egypt	1	0.3	**Romania**	6	2.1
Finland	1	0.3	**Serbia**	3	1
France	1	0.3	**Singapore**	2	0.7
Germany	1	0.3	**Slovenia**	1	0.3
Iceland	1	0.3	**UK**	6	2.1
India	192	66	**USA**	17	5.8
Ireland	1	0.3	**Not Provided**	14	4.8
Italy	3	1			

The variance across group sizes between sample countries mean that direct analysis could not be conducted without further grouping. To resolve this issue and allow cross-cultural comparisons to be made participants where categorized into continent of origin, the sample sizes of each can be in Table 9.2 below.

Table 9.2 Continent Location Grouping summary N

Location Grouping	Total N
Europe	35
North America	24
South America	5
Central Asia	195
SEAsia	17
Africa	1
Not Provided	14

Materials:

The stimulus used in the study consisted of 9 sets of computer generated natural-seeming fractals each with 9 iterations varying in FD (See Figure 9.1 for example set). For full details of stimulus development and experimental design see methodology in Chapter 6. In total, participants made choices for 57 pairs, presented in a randomised order.

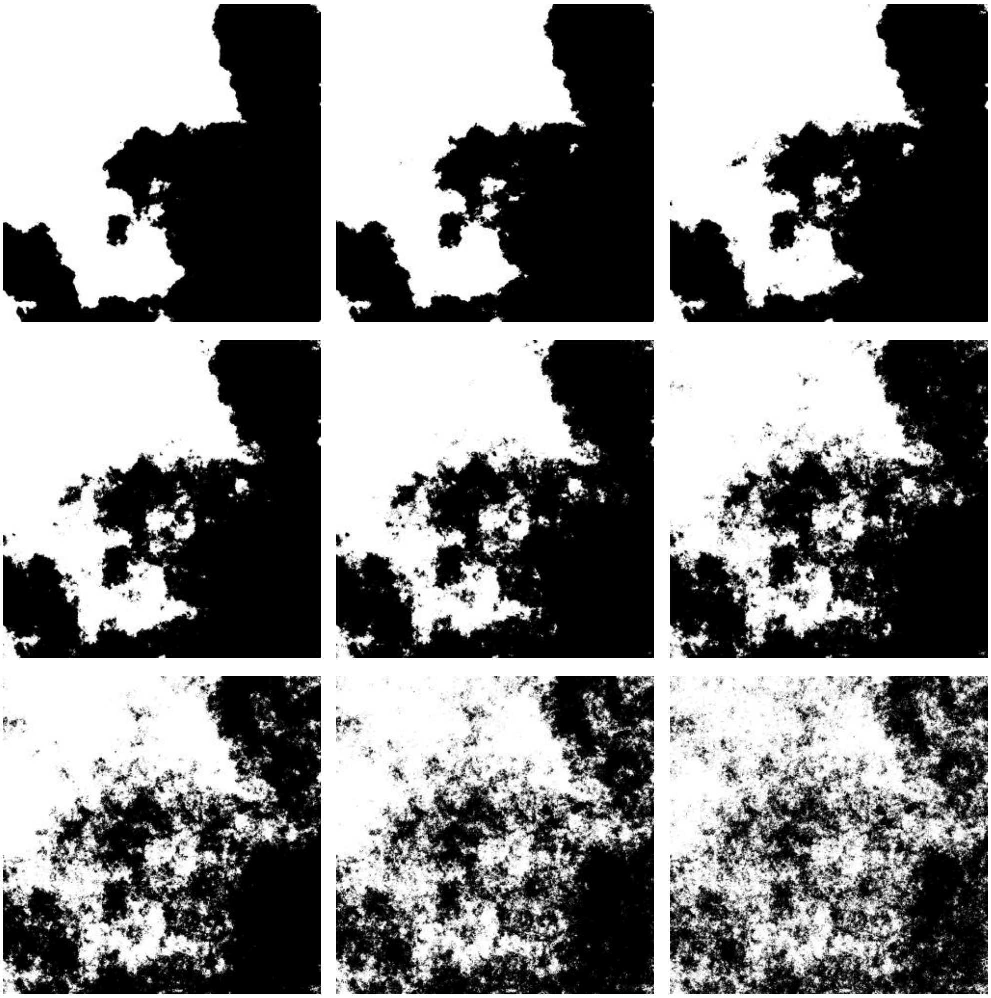


Figure 9.1- Examples of 1 set of Fractal Images

Design:

The study used a between subjects, 2 alternative forced choice design (2A-FC). This method was chosen as an established method of aesthetic judgments (see chapter 6 for full rationale) as the images are not overtly beautiful or appealing, therefore ratings of pleasantness or beauty were not deemed appropriate. Previous research also shows that choice designs are a reliable and easy way to collect preference data with participants consistently able to make judgments without prompts. All data collection was done using an online design, developed and distributed using surveygizmo.com. The link was included on the Mturk recruitment profile and emailed to parties of particular interested groups, such as university students.

Procedure:

Each participant was given an overview of the study details and provided with a link to follow should they wish to volunteer for the study. All participants were asked to read an information page and record electronic consent prior to taking part in the study. After providing demographic information including gender and DOB participants were presented with 57 pairs of fractal images. Each page showed the pair of images and asked the participant to "click the image you like best" (for example see Figure 9.2); this was the same design for each pairing in the study. A choice between the pairing was required for participants to move to the next pairing. After the participants had completed each forced-choice pairing they were taken to a debrief information page to explain the purpose of the study in greater detail and also provided with contact details should they wish to withdraw their results within 2 weeks of completing the study.

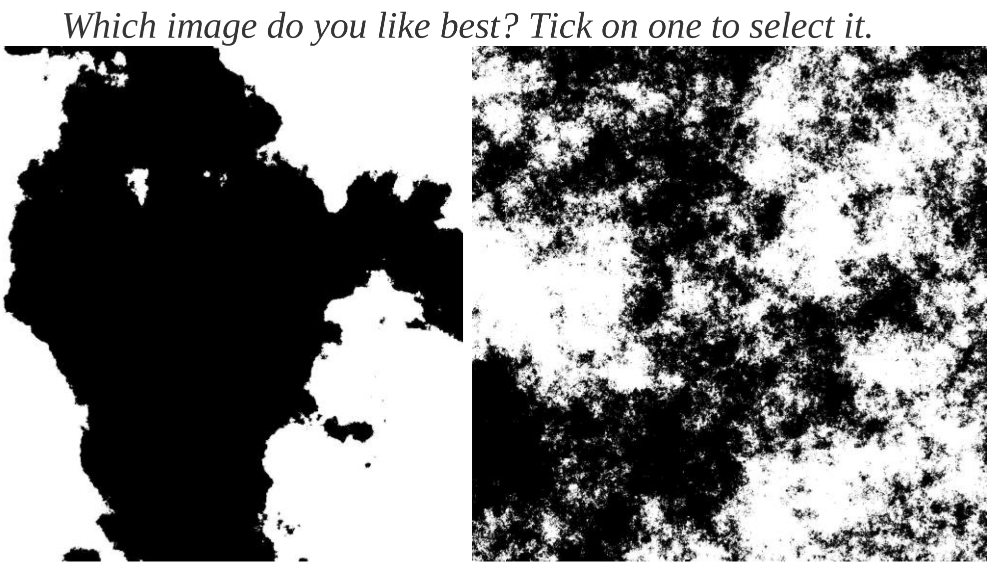


Figure 9.2 – Example of 2A-FC task

9.3 Results:

9.3.1 Exploring the frequencies with ANOVA

The results show that overall preference patterns reflected a curve with peaks at a slightly lower point than previously suggested by Taylor et al., (2011). The highest frequency in choice was seen for D1.2 (M=7.05, SD=3.91) with D1.3 being the next most preferred (M=6.94, SD=3.61). The least variance in scores across the sample was seen over D1.4, D1.5 and D1.6 suggesting that preference is more consistent for these levels compared to the lower and higher D values which appear to have much more variation in preference choice.

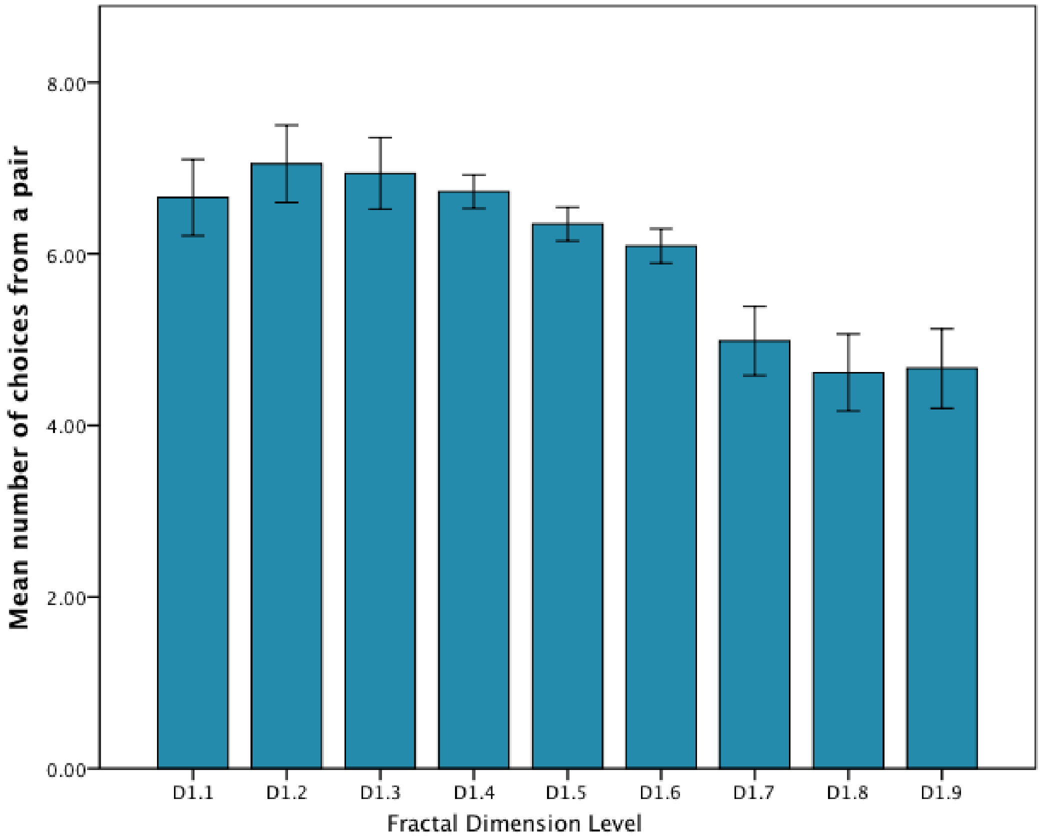


Figure 9.3 Bar Chart displaying the mean number of choices

As demonstrated in Figure 9.3, the overall trend of the data suggests that differences exist between the levels of fractal dimension. The results appear to show that the highest preferences fall at the fractal dimension D1.2 (M=7.05, SD=3.91) and the lowest preference falls at D1.8 (M=4.61, SD=3.87).

Table 9.3 Mean choice scores across each Fractal Dimension

FD	Mean	SD
D1.1	6.66	3.85
D1.2	7.05	3.91
D1.3	6.94	3.60
D1.4	6.72	1.70
D1.5	6.35	1.71
D1.6	6.09	1.73
D1.7	4.98	3.48
D1.8	4.61	3.87
D1.9	4.66	4.01

Mauchly's test indicated that the assumption of sphericity had been violated, $\chi 2$ (35) = 2979.16, $p < .001$, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .183$). The results show that there was a significant effect of fractal dimension, F (1.46, 424.45) = 23.86, $p < .001$, $\eta 2p=0.076$. These results suggest that preference ratings differ significantly between each fractal dimension.

Following this analysis, post hoc pairwise comparisons were performed across the 9 different fractal dimensions to explore the point(s) at which these significant differences can be seen. Table 9.4 demonstrates the significant and non-significant relationships between each level, with the significant differences marked in orange and the non-significant differences marked in white. Analysis found significant differences of preference grouped mainly at the high end of fractal dimension scale. The results suggest clusters in which preference is most variant and that there is less difference in preference choice at the lower end of the fractal scale. The overall analysis demonstrates that preference differs significantly as a function of fractal dimension and that preference within the sample differs most at the end of the Fractal Dimension scale.

Table 9.4: Table of post-hoc differences for Entire Sample.

	D1.1	D1.2	D1.3	D1.4	D1.5	D1.6	D1.7	D1.8	D1.9
D1.1		-.392*	-.282	-.069	.309	.567	1.674*	2.041*	1.993*
D1.2			.110	.323	.701	.959*	2.065*	2.433*	2.385*
D1.3				.213	.591	.849	1.955*	2.323*	2.275
D1.4					.378	.636*	1.742*	2.110*	2.062*
D1.5						.258	1.364*	1.732*	1.684*
D1.6							1.107*	1.474*	1.426*
D1.7								.368*	.320
D1.8									.048
D1.9									

* The mean difference is significant at the Adjustment for multiple comparisons: Bonferroni.

Impact of Gender:

We explore if preference across the Fractal Scale differed significant as a function of gender. Figure 9.4 shows the pattern of preference across the fractal dimension scale for Males and Females in the sample with their mean choices across the scale can be seen in Table 9.5 below.

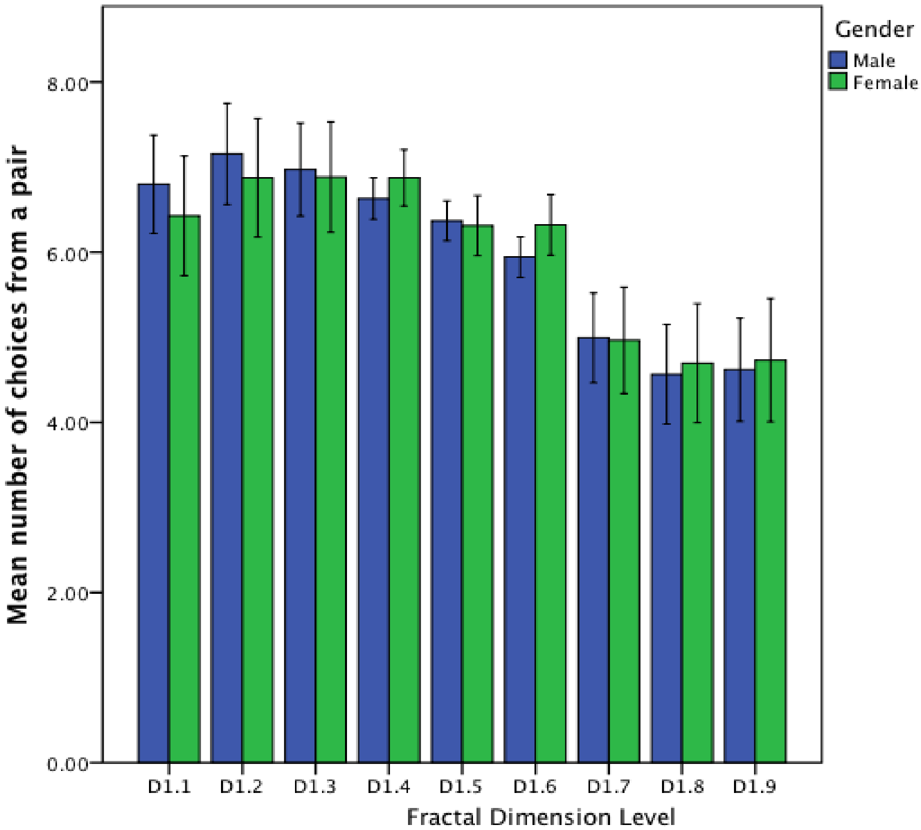


Figure 9.4 Bar Chart of Mean Choice across FD split by Gender

Mauchly's test indicated that the assumption of sphericity had been violated, $\chi 2$ (35) = 2973.40, p < .001, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ε = .183). The results show that there was no significant effect of fractal dimension (F (1.46, 422.47) = .332, p =. 649). These results suggest preference does not differ significantly because of gender.

Table 9.5: Grouped FD Mean scores in preference between Gender grouping.

	Male (N=179)		Female (N=112)	
	Mean	**SD**	**Mean**	**SD**
D1.1	6.79	3.92	6.43	3.75
D1.2	7.16	4.03	6.87	3.72
D1.3	6.97	3.70	6.88	3.46
D1.4	6.63	1.66	6.87	1.77
D1.5	6.37	1.59	6.31	1.88
D1.6	5.94	1.61	6.32	1.89
D1.7	4.99	3.58	4.96	3.33
D1.8	4.56	3.97	4.69	3.74
D1.9	4.62	4.11	4.73	3.87

Impact of Age on Preference:

The age of participants were categorised to allow an analysis of variance between groups Analysis revealed significant differences between age groupings, the means and standard deviations can be seen in Table 9.6 below.

Table 9.6 :Grouped FD Mean scores in preference between Age grouping.

	18-20 (N=30)		21-30 (N=171)		31-40 (N=60)		41-50 (N=14)	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
D1.1	6.23	4.62	6.82	3.63	7.15	3,88	5.50	4.41
D1.2	6.30	4.28	7.32	3.66	7.58	4.07	6.00	4.35
D1.3	6.30	3.96	7.13	3.42	7.42	3.74	5.50	4.01
D1.4	6.87	1.87	6.76	1.69	6.66	1.67	7.28	1.89
D1.5	6.73	1.84	6.33	1.73	6.17	1.52	6.64	1.39
D1.6	6.43	2.08	6.10	1.63	5.75	1.82	6.43	1.45
D1.7	5.73	3.40	4.74	3.38	4.55	3.64	6.00	4.07
D1.8	4.90	4.05	4.43	3.70	4.23	4.02	5.28	4.49
D1.9	4.73	4.09	4.43	3.77	4.50	4.38	5.36	4.81

	51-60 (N=12)		61-70 (N=3)		71-80 (N=1)	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
D1.1	5.33	3.42	1	1	11	-
D1.2	4.83	3.21	.33	.58	12	-

D1.3	6.17	3.21	1.33	.58	10	-
D1.4	5.83	1.11	5.33	.58	7	-
D1.5	5.92	2.35	6.67	1.53	8	-
D1.6	6.08	2.19	7.33	1.15	5	-
D1.7	6.75	2.49	9.67	.58	1	-
D1.8	6.33	2.96	11.66	.57	0	-
D1.9	6.75	3.47	10.67	1.53	0	-

Mauchly's test indicated that the assumption of sphericity had been violated, $\chi2$ (35) = 2856.08, $p < .001$, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .185$). The results show that there was no significant effect of fractal dimension, F (8.89, 420.84) = 2.312, $p =.016$ $\eta2p=0.047$.

Impact of Location on Preference:

The sample included a large spectrum of international participants. As the overall sample results seemed to show variation in preference choices across the levels further exploration of this variation was investigated. Given the number of countries and small sample sizes across each within this international sample, participants were grouped into continents (as the samples from each country where to small to truly represent preference patterns for a cultural population) the breakdown of participant numbers can be found in the methods section above.

The three most populated groups were chosen for comparison including Europe (N=35), North American (N=24) and Central Asia (N=195). The 3 grouping were used to explore the impact country has on preference for fractal patterns in further detail. Table 9.7 below outlined the mean scores for each location group across the 9 fractal dimension scales.

Table 9.7 Mean preference Choice across Continent Group

	Europe (N=35)		North America (N=24)		Central Asia (N=195)	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
D1.1	7.37	3.99	4.16	3.41	7.07	3.67
D1.2	7.66	3.96	5.04	3.77	7.45	3.76
D1.3	7.80	3.58	4.96	3.48	7.18	3.41
D1.4	6.77	1.33	6.87	1.89	6.69	1.66
D1.5	6.40	1.56	6.21	2.10	6.30	1.67
D1.6	5.97	1.48	6.25	1.89	5.94	1.70
D1.7	4.68	3.68	6.83	3.64	4.58	3.27
D1.8	3.46	3.74	6.79	4.08	4.35	3.68
D1.9	3.88	4.10	6.87	4.33	4.37	3.77

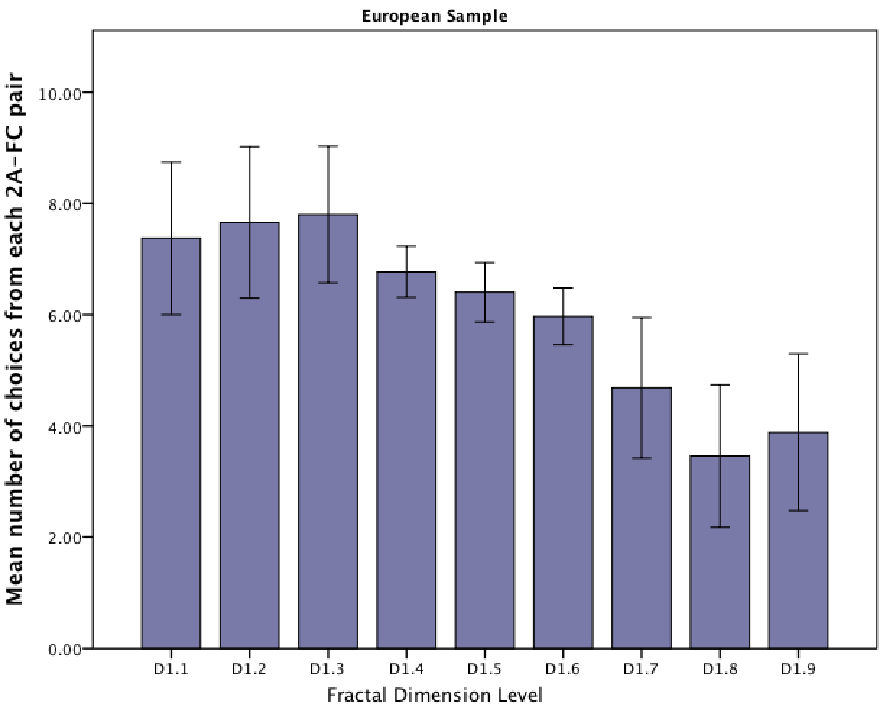


Figure 9.5 Bar Chart of Mean Choice across FD split in the European Sample

The Europe sample demonstrates (see Figure 9.5) preference in a negative linear relationship with fractal dimension. It appears the participants in the sample like the low fractal images (D1.1, 1.2 and 1.3) but after this point preference fell with increased fractal D (or complexity of the image).

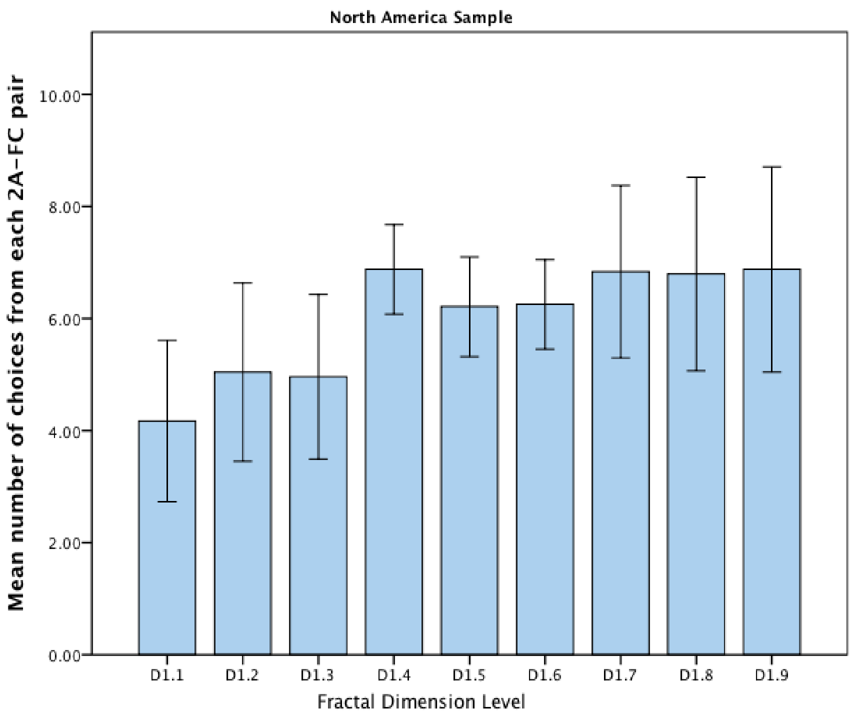


Figure 9.6 Bar Chart of Mean Choice across FD split in the North American Sample

The North American sample demonstrates (See Figure 9.6) a positive linear relationship for Fractal D, complexity and preference, with highest choice and appeal seen in the highly fractal images with less preference shown for the lower fractal images. This data does seem to indicate an increased peak at the mid-point (1.3-1.4D) in line with currently literature however the highest preference is shown for the most fractal image in the sample (D1.9).

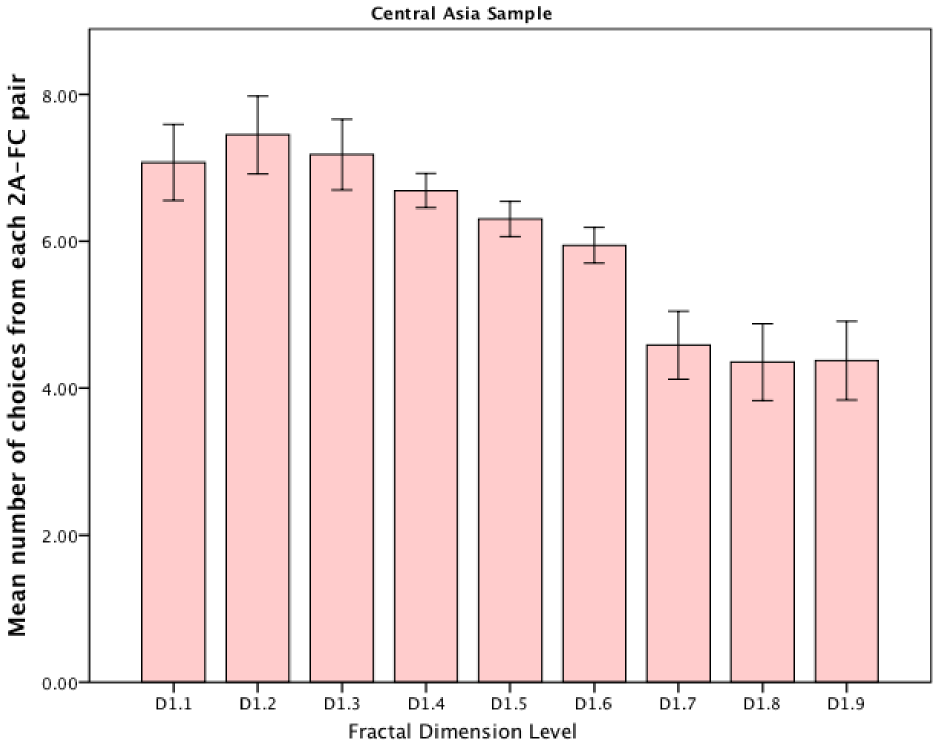


Figure 9.7 Bar Chart of Mean Choice across FD split in the Central Asian Sample

The Central Asia Sample made up the majority of the data set. As demonstrated in Figure 9.7, the highest preference is shown for the lower (D1.2) range of fractal patterns with a sharp drop in choice for images over the D1.6 point. Results suggest a slight linear in preference, with a peak at the lower end of the fractal scale than previous found.

Mauchly's test indicated that the assumption of sphericity had been violated, $\chi 2$ (35) = 2884.82, $p < .001$, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .185$). The results show that there was a significant effect of fractal dimension, F (4.45, 425.84) = 4.41, p = .001, $\eta 2p$=0.044. These results suggest that preference ratings differ significantly between each continent.

Table 9.8 :Table of post-hoc differences across continent.

	Europe	North America	Central Asia
Europe		-1.665	.006
North America			.006
Central Asia			

* The mean difference is significant at the Adjustment for multiple comparisons: Bonferroni.

Following this analysis, post hoc pairwise comparisons were performed across the locations to explore the point(s) at which these significant differences can be seen. No significant differences were found between any pairwise comparisons (see Table 9.8), as ANOVA is a more sensitive test, suggesting that the findings should be taken with caution. This finding demonstrates the issues with using frequency data to explore aesthetic responses when using a 2A-FC design.

Summary:

A linear preference for fractal images is demonstrated within the frequencies of choice is shown based on continent. Europe and Central Asia show a positive linear relationship with a variety of difference in the slope from the peak; positive linear relationship demonstrating highest preferences for lower fractal values and lowest preference for higher fractal values. The North America sample shows a negative linear preference, with highest preference shown for higher fractal patterns and least preference shown for lower fractal patterns. None of the continent grouping demonstrates support for a peak of preference at the mid-range of fractal dimension.

Following the initial exploration of data using the methods outlined above to give an overview of trends in preference for fractal patterns it was decided to reanalyse the data using analytic techniques more suited to the data. The problem of using ANOVA's for categorical data have been well documented (Jaeger, 2008), because of the forced choice designs used in the current study, the study uses in addition a generalised linear mixed effect model, using the principles of logistic regression but controlling for the random variance, considered noise in the ANOVA analysis, of both participants and the stimulus used within the study. The findings of the logit models will be explored below, for a further rationale of using generalised linear mixed models within the 2A-FC design see Chapter 6.

9.3.2 Linear Mixed-effects Modelling:

The method tested the fit of 3 models exploring preference for fractal patterns from two ways. Each model explored if and how well continent (Europe, North America, Central Asia), Gender and Age are at predicting preference for fractal images either falling within Taylor et al's., (2011) defined 'mid-range' peak preference point (D1.3-1.5), falling within a 'equalised mid' range which (D1.4-1.6) or the choice of the most complex image from each set (highest FD/lowest GIF score image) Both participant samples (participant ID) and stimulus display (Fractal Patterns) were analysed as random effect. The model equations are outlined below:

- ***Model A*** - *(Complexity ~ (Continent+gender+cAge)^2 + (1 | ID) + (1| display))*
- ***Model B*** - *(Taylor's MidRange ~ (Continent+gender+cAge)^2 + (1 | ID) + (1| display))*
- ***Model C*** - *(Equalised Midrange ~ (Continent+gender+cAge)^2 + (1 | ID) + (1| display))*

Model A- Complexity

(Complexity ~ (Continent+gender+cAge)^2 + (1 | ID) + (1| display))

Model A explored the extent to which the variables continent, gender and age could predict the effect that the variables for the choice of the more complex images from a pair.

Overall fit of the model:

Analyses compared the variance explained by the fixed and random effects and explore the extent to which these variables explain the variance in the data. Model A accounts for significantly more variance with fixed and random effects (AIC= 6739.1, df=12) than the null model with random effects alone (AIC= 7023.2, df=3), suggesting that the model is improved with the additional variables (χ^2 (9)= 302.1, p<0.01).

Table 9.9 - Results from complexity model analysis

		β	SE	Z	Pr(>|z|)
Complexity Hypothesis	**Intercept**	-4.497	0.525	-8.55	<2e-16***
	Continent (c-e)	0.389	0.439	0.885	0.376
	Continent (n-e)	1.286	0.579	2.221	0.0264*
	Gender (m-f)	0.062	0.516	0.120	0.9043
	Age	-0.005	0.032	-0.153	0.8782
	Continent (c-e) x Gender (m-f)	0.053	0.557	0.095	0.9244
	Continent (n-e) x Gender (m-f)	-0.514	0.769	-0.669	0.5038
	Continent (c-e) x Age	0.019	0.031	0.603	0.5468
	Continent (n-e) x Age	0.011	0.035	0.300	0.7642
	Gender (m-f) x Age	-0.013	0.020	-0.648	0.5171

*Significance Codes: ***0.001, **0.01, *0.05.*

Additional goodness of fit analysis for each variable found that Continent significantly added to the overall fit of the model (χ^2 (6)= 300.57, p<0.01) however

Gender (χ^2 (4)= 1.721, p=0.787) and Age (χ^2 (4)= 0.9057, p=0.9237) do not significantly add to the overall prediction of the model.

Main Effects Complexity Model:

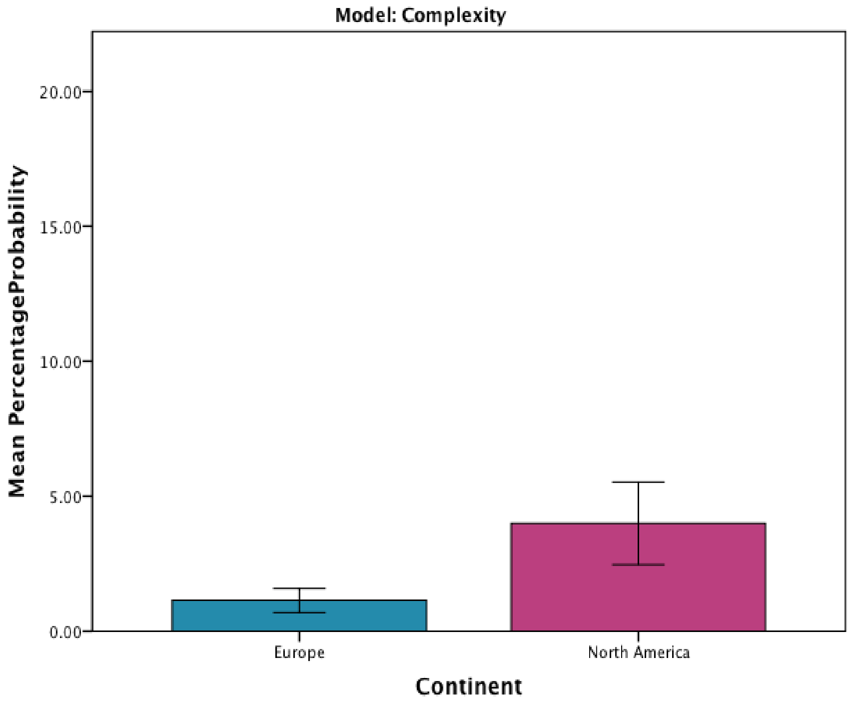


Figure 9.8 Percentages of choice for complex image from a pair between Europe and North American Sample

Main Effect of Continent:

The analysis found significant difference between the 2 continents (Europe & North America) within the sample and location influenced choice of complexity (β = 1.286, z = 2.221, p = 0.026) with European participants having around 1.1% of choosing the complex image from the pair and the North American participants have a 3.8% of choosing the complex image from the pair.

Model B- Mid-Range Model

(Taylor's MidRange ~ (continent+gender+cAge)^2 + (1 | ID) + (1| display))

Model B explored the extent to which the variables continent, gender and age could predict the effect that the variables for the choice of the images falling within Taylor's Mid-Range from a pair.

Overall fit of the model:

Analyses compared the variance explained by the fixed and random effects and explore the extent to which these variables explain the variance in the data (results below in Table 9.10). Model B is accounts for significantly more variance with fixed and random effects (AIC= 11585, df=12) than the null model with random effects alone (AIC= 12088, df=3), suggesting that the model is improved with the additional variables (χ^2 (9)= 521.58, p<0.001).

Table 9.10- results from mid-range model analysis

		β	SE	Z	Pr(>|z|)
Mid-Range Hypothesis	**Intercept**	1.874	0.663	2.828	0.005**
	Continent (c-e)	0.118	0.209	0.564	0.572
	Continent (n-e)	0.741	0.284	2.610	0.009**
	Gender (m-f)	0.160	0.245	0.653	0.514
	Age	0.001	0.015	0.060	0.952
	Continent (c-e) x Gender (m-f)	-0.051	0.266	-0.193	0.847
	Continent (n-e) x Gender (m-f)	-0.746	0.377	-1.979	0.048*
	Continent (c-e) x Age	0.013	0.015	0.878	0.379
	Continent (n-e) x Age	0.016	0.016	0.980	0.327
	Gender (m-f) x Age	-0.008	0.010	-0.828	0.408

*Significance Codes: ***0.001, **0.01, *0.05.*

Additional goodness of fit analysis found that Continent significantly added to the overall fit/prediction of the model (χ^2 (6)= 514.75, p<0.001) however Gender (χ^2 (4)= 7.702, p=0.103) and Age (χ^2 (4)= 4.94, p=0.293) do not significantly add to the overall prediction of the model.

Main Effects Mid-Range Model:

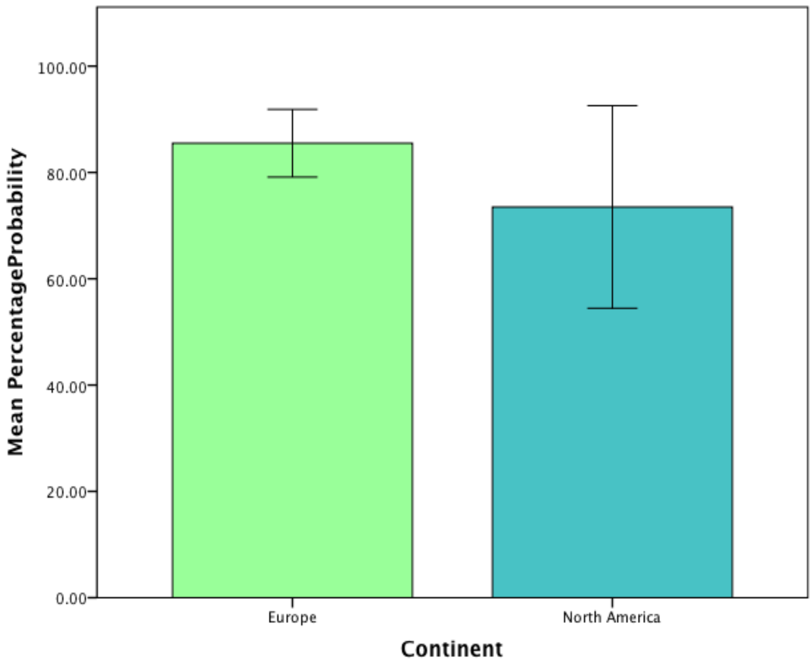


Figure 9.9 Percentages of choice for mid-range image from a pair between Europe and North American Sample

Continent:

The analysis found a significant difference across 2 continents within the sample (β = 1.874, z = 2.828, p < 0.005) with European participants having around 87% probability of choosing the mid-range image from the pair and the North American participants have a 75% probability of choosing the mid-range image from the pair (See Figure 9.9).

Interaction Effects:

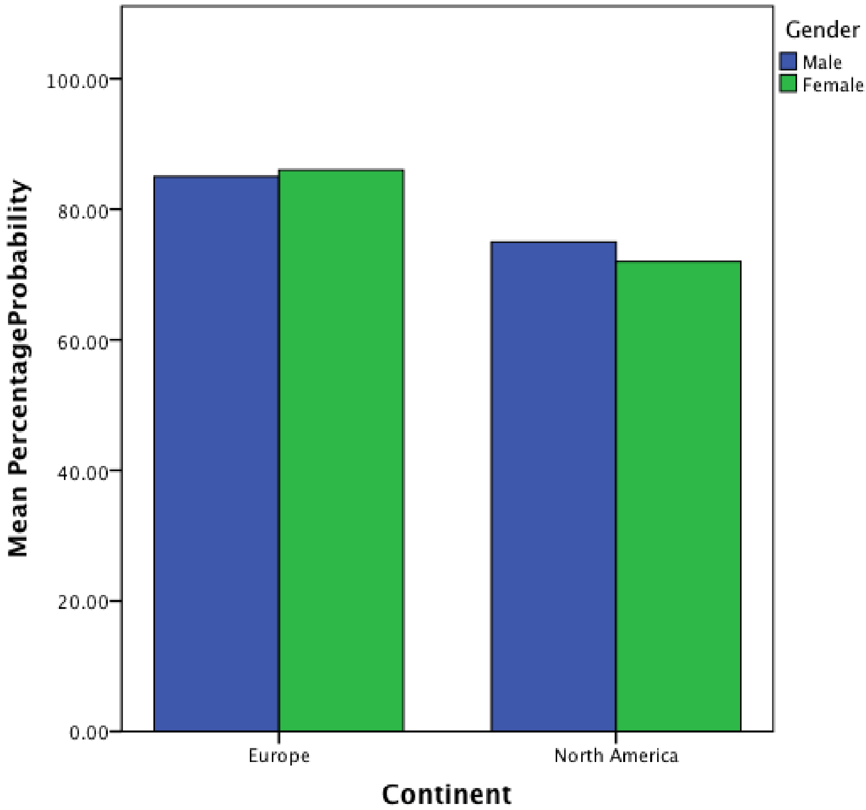


Figure 9.10 Percentages of choice for mid-range image from a pair across continent and gender groups

In addition to the significant main effects of continent, the analysis shows a significant interaction between Continent (North America & Europe) and Gender (β = -0.746, z = -1.979, p = 0.048). As demonstrated in Figure 9.10, European females have an 86% probability of selecting the mid-range images and European males have an 85% probability. Within the North American sample males have a 75% probability whilst females have a 72%. We see differences in preference pattern across the 2 samples in gender and preference for the mid-range.

<u>Model C- EqualizedMid-Range Model:</u>

(EqualizedMidRange~ (continent+gender+cAge)^2 + (1 | ID) + (1| display))

Model C explored the extent to which the variables continent, gender and age could predict the effect that the variables for the choice of the images falling within Equalized Mid-Range from a pair.

Overall fit of the model:

Analyses compared the variance explained by the fixed and random effects and explore the extent to which these variables explain the variance in the data. Model C is account for significantly more variance with fixed and random effects (AIC= 15504, df=12) than the null model with random effects alone (AIC= 16211, df=3), suggesting that the model is improved with the additional variables (χ^2 (9)= 724.54, p<0.001) (See Table 9.11).

Table 9.11- results from equalised mid-range model analysis

		β	SE	Z	Pr(>|z|)
Equalised Mid Hypothesis	**Intercept**	1.563	0.473	3.304	0.001***
	Continent (c-e)	0.078	0.108	0.720	0.471
	Continent (n-e)	0.222	0.147	1.512	0.130
	Gender (m-f)	0.135	0.127	1.068	0.285
	Age	-0.003	0.008	-0.370	0.711
	Continent (c-e) x Gender (m-f)	-0.093	0.137	-0.675	0.499
	Continent (n-e) x Gender (m-f)	-0.402	0.194	-2.066	0.039*
	Continent (c-e) x Age	0.006	0.008	0.762	0.446
	Continent (n-e) x Age	0.008	0.009	0.940	0.347
	Gender (m-f) x Age	0.002	0.005	0.319	0.749

*Significance Codes: ***0.001, **0.01, *0.05.*

Additional goodness of fit analysis found that Continent significantly added to the overall fit/prediction of the model (χ^2 (6)= 709.49, p<0.001) however Gender (χ^2

(4)= 5.0579, p=0.2814) and Age (χ^2 (4)= 3.1719, p=0.5295) do not significantly add to the overall prediction of the model.

Interaction Effects:

The results of the model demonstrate no main effects of the predictor variables and the participant's likelihood to select an equalised-mid range (EMR) image. The results do however demonstrate a significant interaction effect of Continent (North America - Europe) and Gender (Male - Female) on preference judgments (β = -0.402, z = -2.066, p <0.05), suggested that preference for EMR is a function of both continent and gender together (See Figure 9.11).

The direction of the estimate suggests that Female European participants show an 82% choice to prefer the Mid-Range images and Males have an 80% choice. Within the North American participants the opposite gender effects are present with North American Males are more likely (76%)to choose the Mid-Range than Female (73%) North American participants.

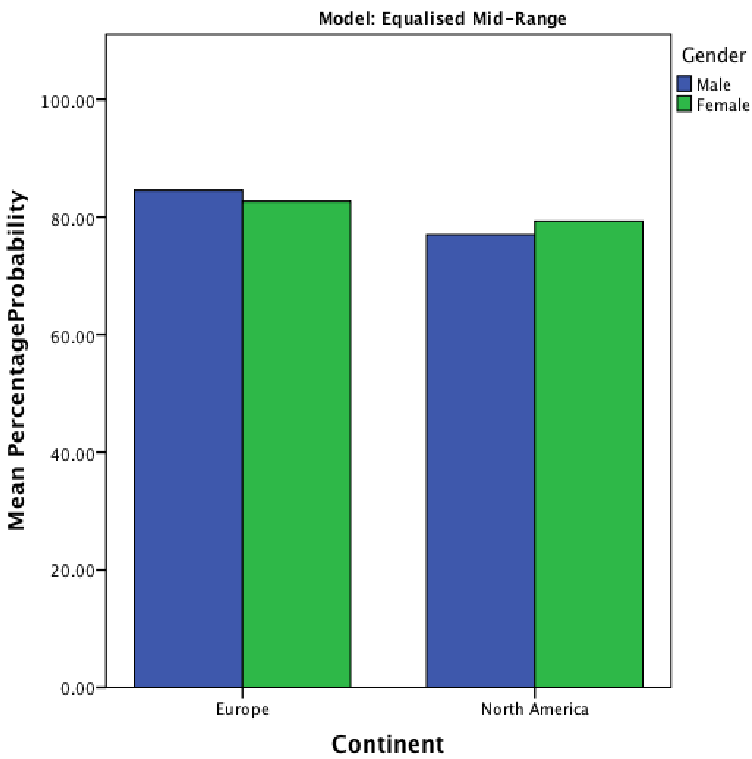


Figure 9.11 Percentages of choice for EMR image from a pair across continent and gender groups

Overall Summary of Results:

The results demonstrate that continent; particularly the differences between North American and European participants and gender are significant predictors of differences in preference for fractal images. Overall these findings suggest that individual differences exist between participants based on Gender and the Continent in which participants live. None of the 3 models have evidence to support differences across age suggesting age (within this limited range sample) does not significantly influence differences preference.

When testing Taylor et al's., (2011) mid-range hypothesis we see high choices towards the mid-range images (Approx. 70-80% across all participants). The analysis finds significant differences in probability of preference choice across continent with European participants demonstrating higher probability of a mid-range choice than the North American participants. There was no significant difference between European and the Central Asian samples. Interactions were found between gender and continent (Europe - North America) and gender with opposite preference patterns with European males being less likely than European females to select a mid-range image and North American females being less likely than North American males. The EMR model found similar percentage probability as Taylor's mid-range model towards selecting the equal mid images (70-80%) however there was no main effect across continent, gender or Age. Finding did show a significant interaction between patterns of preference across gender and continent with opposite male and females showing the greater patterns of preference in different directions in across the 2 continents. As a comparison, the complexity model demonstrates a cross-continental difference in preference, with European participants being significantly less likely to select the complex images from the pair than the North American participants. Both groups have very small probabilities of selecting the complex image from the pair, demonstrating a negative relationship between fractal complexity preference selections.

To summarise the results, the mid-range and complexity models found significant main effect of continent on preference, whereas the EMR model did not show this variance in preference. Both mid-range models found an interaction between gender and continent. Results provide some support for the notion that preference for fractal patterns in mediated by individual differences.

9.4 Discussion:

This study attempted to replicate findings from previous literature suggesting preference is centred at the mid-point in fractal dimension scale (Taylor et al., 2011). The results allow an insight into the cross-cultural stability of fractal preference, proposed as universal by previous literature (Spehar et al, 2003, Berlyne, 1977). The international sample used in this study offered an opportunity to explore if preference patterns differ from cross-country samples. The study also aimed to explore the patterns of fractal preference with the specific aim to investigate Berlyne's inverted-U, and Taylor's mid-range preference hypotheses. The main findings from the study (both frequency data and modelled data) show significant individual differences can predict differences in preference for fractal patterns across culture with some interaction between country and gender.

Mid-Range Models:

The frequency analysis did not find evidence to support the mid-range hypothesis previously found in literature for fractals and complexity (Taylor et al., 2011; Berlyne, 1977), the patterns of preference instead seem to point towards a negative linear relationship between fractal dimension and preference choice. Additional analysis explored two models; the findings demonstrate some support for the mid-range preference for complexity or fractal dimension. Aks & Sprott (1996) suggest that people's preference is universally set at D1.3 because of continual visual exposure to nature's patterns others argue that observers demonstrate preference at a lower D value because these scenes mimic the properties of African Savannah scenery, were our ancestors spent a large part of their evolutionary history (Wise & Leigh-Hazzrd, 2000). The findings of this study however dispute that preferences are set at D1.3, and instead appear to be variable dependent on the continent in which you reside.

Complexity Models:

To allow comparisons to be made, an additional pattern of preference was explored in the analysis. This model aimed to explore the likelihood of participants choosing the most complex image from a pair. Previous literature has shown that preference for complexity falls in a linear relationship with higher preferences being shown for higher complexity in some stimulus (Forsythe et al, 2008). The present findings do not support this hypothesis and as evidence in the frequency analysis, show instead a negative linear relationship with preference choices being most prominent for the lower FD values and falling at the higher end of the fractal scale. Analysis have found there is significant difference in this direction however across culture. Further modelling of the data allowed us to calculate the choice percentage scores of participants selecting the more complex image from the pair and found that these are very low across the sample, particularly for the European sample when the complex image of a pair was only selected 1% of the time. These findings suggest that the participants disliked the complexity within the images in the study and instead appear to show a strong preference towards the simpler stimulus images when making a preference choice. Linear patterns of preference with complexity have been found within previous studies in this thesis, Chapter 8 explores the impact of country on preference for fractal patterns using a rating scale design, and the results suggest a negative linear relationship between Egyptian participants and fractal complexity with a more variance and equally distributed preference patterns shown for the UK sample. The strength of these findings raises questions about the stability of the mid-range hypothesis as a universal model of fractal preference and instead suggests a negative linear relationship between fractal complexity and preference as a strong contender to this established theory.

Continent Difference in Preference:

Continent emerged as a significant predictor of preference for fractal complexity over the lower and simpler fractal images within the stimulus set. Participants from North American and Europe differed significantly with results suggesting negative linear relationships between each continent and preference for complexity.

Theoretical links, explaining the Patterns of Preference:

The ecological variant theory that exposure to environmental patterns of complexity or those that display fractal properties could potentially be influence and shape aesthetic responses. The mere exposure hypothesis (Zajonc, 1968) states that that exposure to stimulus can result in heightened preferences as we demonstrate higher aesthetic judgment to familiar objects, patterns of scenes. Reber et al., (2004) proposed a processing fluency model, which may account for increased preference with mere exposure as they suggest familiarity results in ease of processes that are hedonically marked. The current findings show significant differences for complexity across continents and this could be suggested to be a result of the different visual experience those residing in different continents may have, this conclusion brings into question the impact environmental exposure has on our preferences for shapes and structures. Not only on larger macro-scales such as continent and country, but also in terms of smaller micro-scales such as the daily visual experiences from home, work and socializing. The environmental classification in which a person lives, or develops may impact our preference for fractal patterns. As fractal patterns are commonly found in nature, those who develop and live in rural setting are regularly viewing complex fractal patterns (in trees, plants and natural landscapes), people who spend much of their time in urban environments have little exposure to fractal patterns, as man-made structures such as roads, buildings and computer screens do not display fractal complexity. Based on Zajonc (1968) mere exposure hypothesis it could be suggested that higher preference will be shown for the scenes that resemble those you see regularly, therefore urban participant show preference for simple fractal patterns (based on the lack on complexity in their daily visual field) and participant in rural environments will show preference for more complex higher fractal patterns because of the complexity they see in their environment. This assertion needs further testing, the environments in which participants spend most of their time should be investigated to explore if exposure to natural patterns, or lack there of, could be accountable for the differences in linear preference found in this study.

Continent and Gender interactions:

Further to the differences between continents and preference for complexity discussed above, the results also found two cases of interaction between continent and gender at predicting aesthetic responses to fractal patterns. The role that continent may play on preference has been explored above, however results demonstrate that gender is a strong predictor alongside continent to complex and mid-range fractal patterns. It appears that perceptual styles or affective processing may result in significant differences in aesthetic response between gender, one study found that paintings that showed behaviour evoked more pleasure and attention among female participants over male participants (Fedrizzi, 2012). The author suggests that neuroanatomical studies can enhance the comprehension of why such gender differences appear to exist (Fedrizzi, 2000) and other evidence demonstrating gender differences in cognitive processes (Leder et al, 2004) support this claim.

Cela-Conde et al., (2009) found gender-related differences in parietal activity during aesthetic appreciation and judgments. These results suggest that there are difference in the way males and females process aesthetic appreciation, although specifying how the differences manifest in response is challenging and yet to be explored in great depth. When looking at landscape preferences, gender differences have been found previously (Kellert, 1978; Lyons; 1983) some suggest these differences in response to landscape between men and women may have evolutionary roots. Silverman and Eal's (1992) hunter-gather hypothesis offers one possible explanation for the differences in perceptual strategies and therefore aesthetic responses. The theory outlines that gender differences in spatial ability is a qualitative result (rather than any quantitative differences) of the different tasks of the sexes in hunter-gather tasks. Spatial skills associated with hunting are more developed in males and females show heightened peripheral perception and incidental memory for locations and objects because of the gathering tasks. Further findings suggest that males look at the whole picture during aesthetic judgment, where as females tend to pay attention to smaller details within the picture (Cela-Conde et al 2009). Perceptual style and the perceptual features of the artwork have been found to be consequential to aesthetic judgments (Boccia et al., 2014).

Limitations of study:

The study has made some intriguing findings but does have some limitations, which will be discussed briefly and reflected upon for future studies within this thesis. One such limitation is the grouping into continents of the participants; it is acknowledged that using continent, as the grouping is a rough method of grouping based on available data, the author demonstrates an awareness that environments within continents and within countries have a lot a variation, and highlight the need for future research to be focused on the factors within environments, such as rural, urban or suburban settings to attempt to unpick the role environment plays in preference for fractal patterns. In addition to this grouping limitation, as most participants (62%) were recruited from India it was recognized that this sample had the most impact on the preference patterns found in the overall sample results. However despite the invariance, the largest differences were found between North America and Europe, rather Europe and the most populated continent of Central Asia.

The results offer conflicting evidence to the current trends and findings with the field of empirical aesthetics, which have previously found preferences for the mid-range to be relatively stable across individual variation. The findings show that preference for complexity is low (between 1-3%) within the sample, however there are significant differences in the probability of choosing (or not choosing) a complex image from the pair across culture. The mid-range findings show that people do indeed have higher preference for the mid-range model as probability fall within the higher percentile (around 80%). This probability however when compared to the complexity model likelihood (or unlikelihood of almost 99% not choosing the complex image) there appears to be some difference between the fit of the models to the data.

Conclusions:

The results of this study show that fractal dimension can be a predictor of preference for natural looking computer generated stimulus, however the patterns of this preference seem to be influenced by individual differences in participants suggesting that visual environment (continent) and gender may also play a role in influencing our aesthetic choices.

10.0 Optimal Fractal Preference; Stability across culture and within sub-cultural visual environments

This study aims to explore the links between macro-cultural environment (UK/Egypt) and mirco-cultural environment (urban/rural), as well as gender and age as predictors of preference for fractal patterns. Previous studies in this thesis demonstrate linear relationships between fractal dimension and preference dependent on the continent in which participants reside (Chapter 9) whereas as previous literature suggests images within a mid-range fractal dimension will be universally preferred (Spehar et al, 2003;Taylor et al, 2006). This study explores two groups of participants from the UK and Egypt, residing in rural, urban and suburban environments within each of the two countries. The study used a 2A-FC online design, and samples were recruited using opportunities samples at universities. The results show there was no significant difference in preference based on country. Significant differences however were found between participants in the rural and urban groups. The rural groups shows higher preference for higher complex FD (Fractal Dimension) images with much lower preference for lower complexity FD images and the urban group shows a linear relationship in the opposite direction in which lower complexity FD images were most preferred and higher complexity FD images least preferred. These results suggest that visual environment and the patterns we are exposed to have significant involvement in our how our preferences are shaped rather than any particular cultural quality of the countries in which we reside. The results offer support for cognitive exposure theories of preference and offer a conflicting account to current literature in the field regarding the universality or evolutionary theories of preference shaped around the mid-point of fractal scales.

10.1 Background & Rationale:

Chapter 9 investigated the stability of the mid-range hypothesis of fractal preference in re-testing. The results raised questions on the universality of preference across culture. Results did not support an inverted U-shaped preference with optimal peak in appeal at the mid-range, as suggested in previous literature. Instead a linear relationship was found which differed significantly in the direction between continent groupings. With some groupings (Europe & Central Asia) preference demonstrated a negative linear relationship in which preference decreasing with fractal dimension. Alternatively other samples (such as North America) demonstrated a positive linear relationship, in which preference is lowest for the lowest FD stimulus and highest for the most complex FD stimulus.

The present study aims to confirm and explore the linear preference relationship found in previous studies in further detail. It uses two targeted cross-cultural samples (UK and Egypt) to explore the influence of culture on preference. In addition, within-culture sub-groups will be used to explore the impact of visual environment on preference. Participants will be recruited from differing environmental classifications (rural, urban and suburban). The sample aims to show whether differences in preference are influenced by our immediate micro-visual environment (for example where we live) or by our more general macro-visual environment (a more generalized view of the culture in which we live). Finally this study explores the use of additional measures of complexity when investigating the preference shown for fractal images. As the two concepts of fractal dimension and complexity both influence our aesthetic responses, it was decided that alongside fractal dimension measured complexity models would also be explored to examine the correlations between fractals and complex in our visual experiences.

The research aims to explore the impact of cross-cultural and sub-cultural environment of visual preferences for complex natural shapes as well as the potential impact of gender and age. The area currently has conflicting findings based from distinct disciplines with little interdisciplinary cross-over, it is hoped that this research will go some way in exploring the inconsistencies and offer a more rounded approach to understanding aesthetic relationships with fractal patterns.

10.2 Methods

Participants: In total 80 participants took part in the study. Participants were recruited through opportunity sampling through university student Internet communication.

UK Sample: 47 participants were recruited for the UK Sample via electronic communication. The UK sample has a mean age of 21yrs, and contained 12 male & 35 female participants. Participants were asked to classify the environment they resided in; From the UK sample 15 participants classified their environments as ‘urban’, 17 stated ‘rural’, 13 ‘suburban’ and 2 participants felt their environment was ‘other’.

Egypt Sample: 33 participants were recruited for the Egypt sample from Monufia University. Students were recruited using online communication. The Egypt sample had a mean age of 20yrs and contained 16 males and 17 females. When participants were asked to classify their environment, 8 stated their environment was ‘urban’, 22 as ‘rural’ and 3 classified as ‘suburban’.

Materials: The stimulus used in the study consisted of 9 sets of computer generated natural-seeming fractals each with 9 iterations varying in FD (*See Figure 10.1 for example set*). For full details of stimulus development and experimental design see chapter 6. In total, participants made choices with 57 pairs were presented in a randomised order.

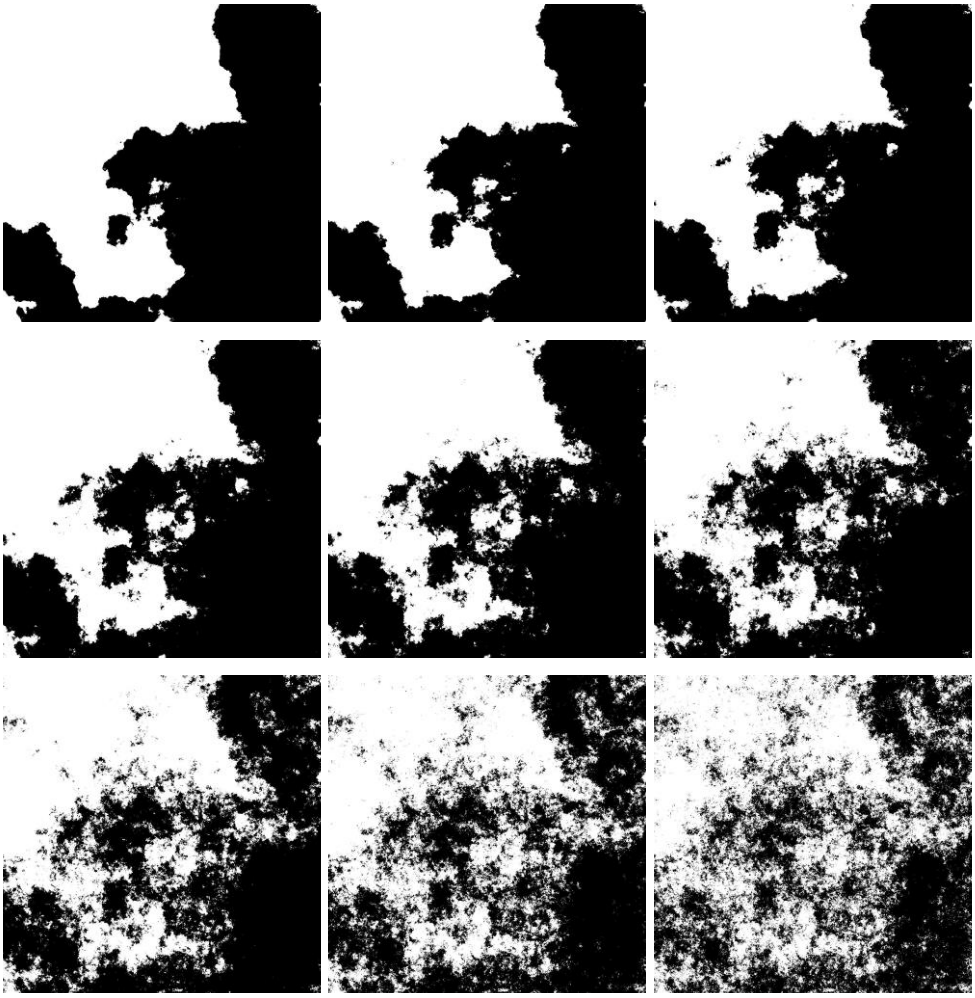


Figure 10.1- Example of 1 full set of Fractal stimulus used in study

Design: The study used a between subjects 2 alternative forced choice design (2A-FC). This method was chosen as an established method of aesthetic judgments (see chapter 6 for full rationale). All data collection was conducted online and distributed through university communication systems for recruitment. The website surveygizmo.com allowed the design, development and distribution of the survey online.

Procedure: Each participant was given an overview of the study details and provided with a link to follow should they wish to volunteer for the study. All participants were asked to read an information page and record electronic consent prior to taking part in the study. After providing demographic information including environment classification (Urban, Rural, Suburban or Other), Country of residence (UK or Egypt), gender and Age. Participants were presented with 57 pairs of fractal images. Each page showed the pair of images as asked the participant to “click the image you like best”; this was the same design for each pairing in the study. A choice between the pairing was required for participants to move to the next pairing. After the participants had completed each forced-choice pairing they were taken to a debrief information page to explain the purpose of the study in greater detail and also provided with contact details should they wish to withdraw their results within 2 weeks of completing the study.

10.3 Results

10.3.1 Patterns of preference

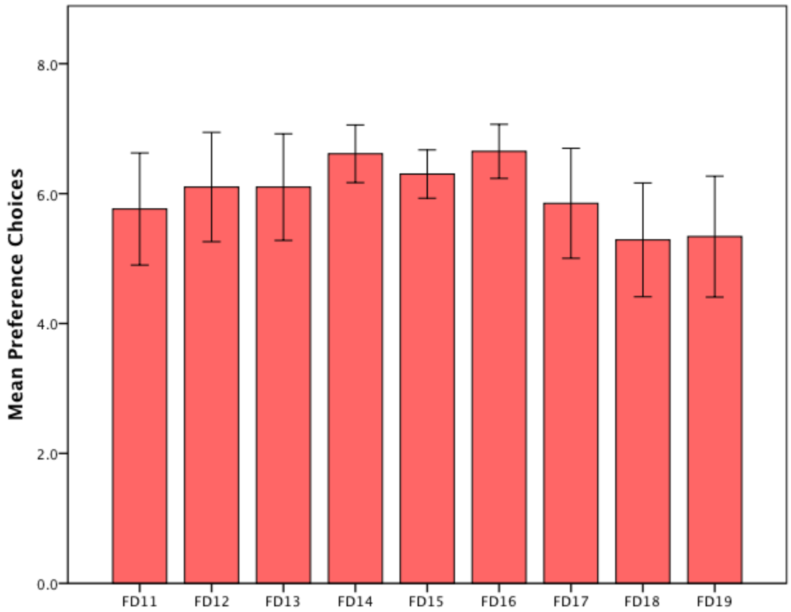


Figure 10.2 Bar Chart of Overall Preference patterns across the fractal scale.

The initial analysis of this study involved exploring the frequency of choice across the full fractal scale used in the study. This analysis (whilst the limitations are acknowledged) offers a way to explore the patterns of preference to allow comparison between the mid-range and linear complexity hypotheses.

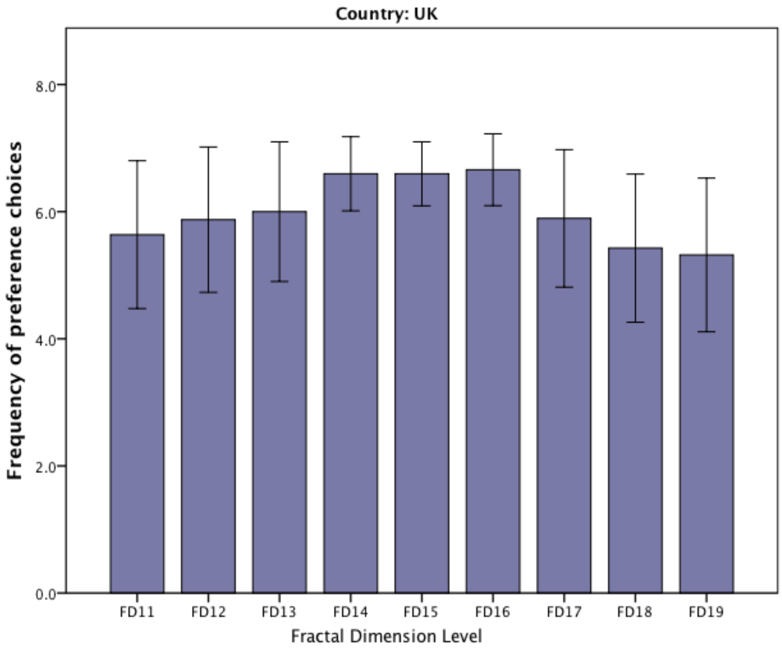


Figure 10.3 Frequency of overall preference choice (UK)

Looking at the UK sample (See Figure 10.3) we see the highest number of choices fall at the mid-range of the fractal scale with the peak relatively high within this area (D1.6, M=6.66, SD=1.92) and preferences fall lowest towards the low-end (D1.1, M=5.64, SD=3.95) and high-end of the scale (D1.9, M=5.32, SD=4.11). Additional analysis however found no significant differences across any of the difference levels in choice frequency (Mauchly's test indicated that the assumption of sphericity had been violated, $\chi 2$ (35) = 510.857, p <0.001, the Greenhouse-Geisser adjustment was therefore applied ε=.187, F(1.49, 68.68)=0.970, p=.362).

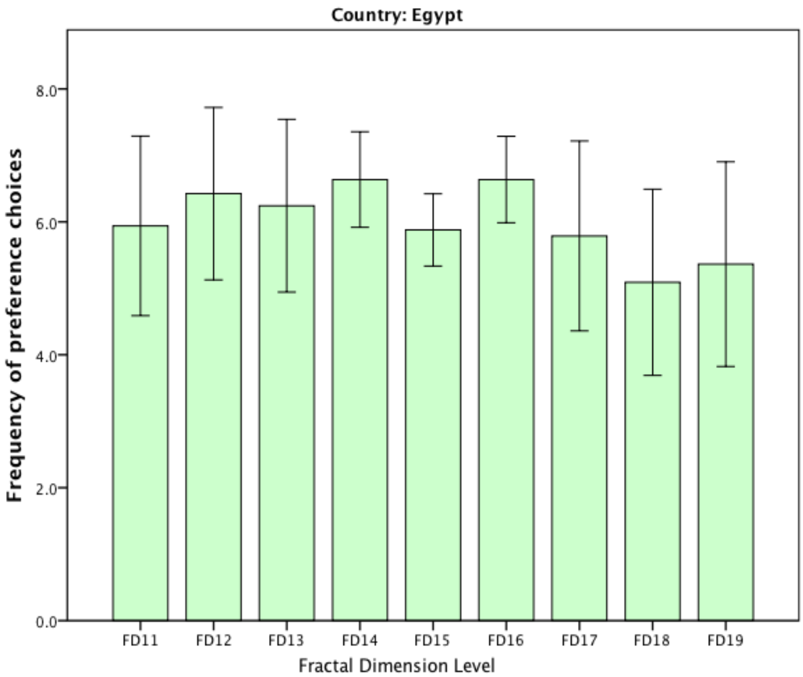


Figure 10.4 Frequency of overall preference choice (Egypt)

Within the Egyptian sample (See Figure 10.4), preference appears more varied across each fractal level. Preference choice peaks equally at both D1.4 (M=6.34, SD=2.03) and D1.6 (M=6.36, SD=1.83) with preference choices falling lowest at D1.8 (M=5.09, SD=3.95). Additional analysis however found no significant differences across any of the difference levels in choice frequency (Mauchly's test indicated that the assumption of sphericity had been violated, $\chi 2$ (35) = 300.33, p <0.001, the Greenhouse-Geisser adjustment was therefore applied ε=.192, F (1.54, 49.14)=0.759, p=.441).

Gender Differences in Frequency of Preference Choices:

Repeated measures ANOVA found differences in mean preference choices between Male and Female participants. Within the Male sample preference choice peaks at D1.4 (M=7.107, SD=1.79) and decreases with increases in fractal dimension level with the lowest choices for the highest fractal stimulus (D1.9 M=4.14, SD=3.99) (See Figure 10.5).

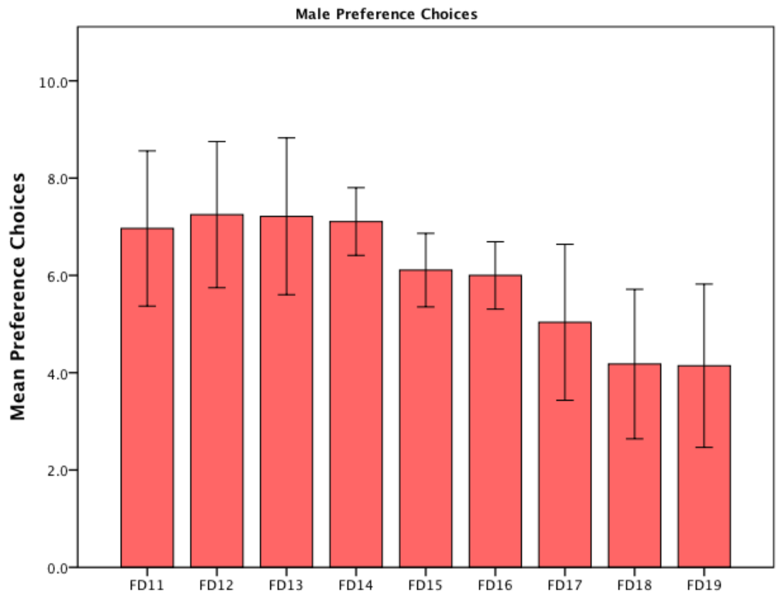


Figure 10.5 Bar Chart of preference choices across fractal scale in Male Participants

Within the female sample (See Figure 10.6) preferences peak at a later point at D1.6 (M=7.00, SD=1.85) and preference choice falls from a peak point with the least preference choice for the lowest FD level (D1.1 M=5.11, SD=3.62).

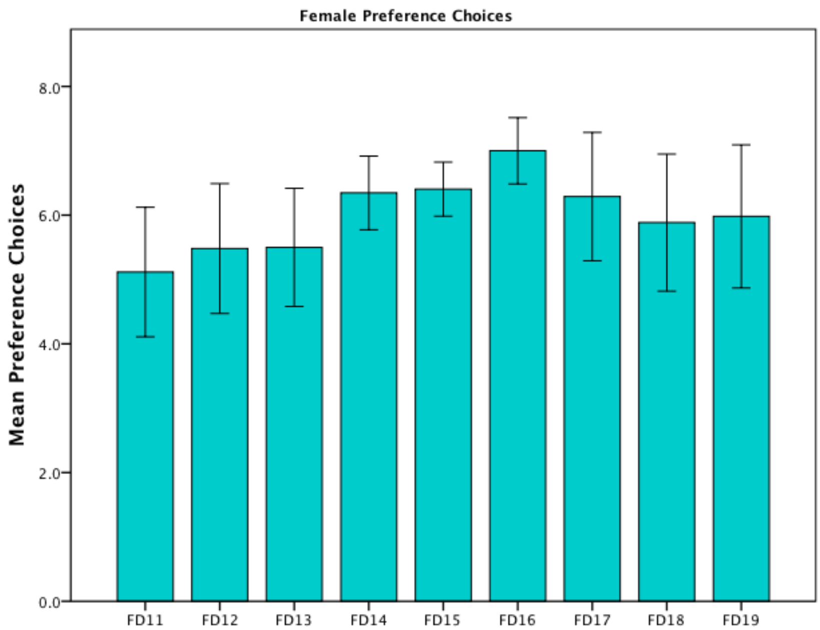


Figure 10.6 Bar Chart of preference choices across fractal scale in Female Participants

Mauchly's test indicated that the assumption of sphericity had been violated, $\chi 2$ (35) = 782.17, p <0.001, the Greenhouse-Geisser adjustment was therefore applied ε=.193, Analysis found significant difference between gender and fractal dimension (F (1.54, 120.26)=3.55, p=.043).

Environmental Classification:

The patterns of preference were also explored across the environmental classification. It was hypothesised that this micro-cultural split would yield preference choice differences because of visual differences in the environment because of the presence (or lack-there-of) of fractal patterns.

Urban: As demonstrated in Figure 10.7, the participants identifying themselves as 'Urban' show preferences that group at the lower end of the continuum and peak at D1.3 (M=7.91, SD=3.76), and falls (nearly) incrementally from this point with the lowest preference choice at the highest end of the scale (D1.9 M=3.69, SD=4.07). This pattern of preference points towards a negative linear relationship between complexity and preference choice.

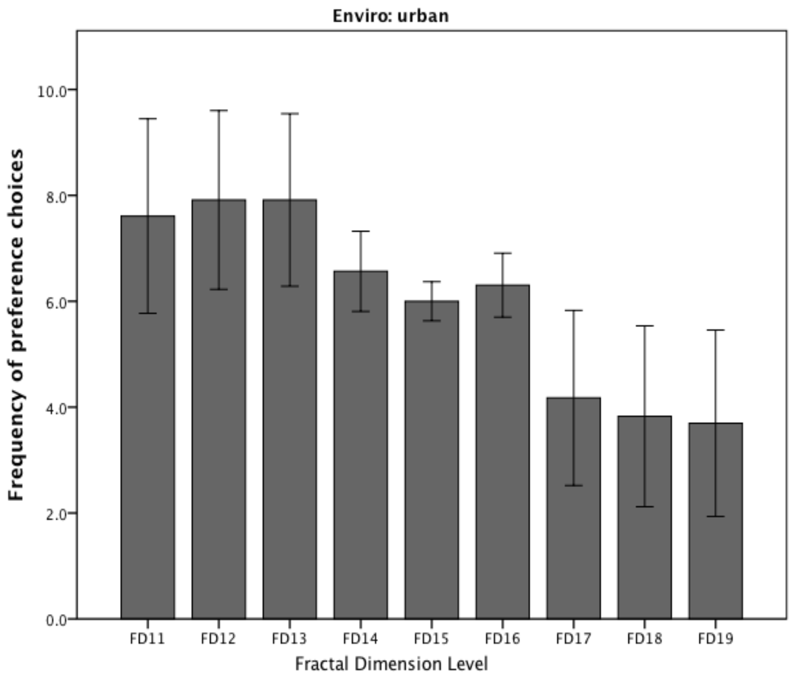


Figure 10.7- Bar Chart of preference choices across fractal scale in urban sample.

Rural: As demonstrated in Figure 10.8, the participants identifying themselves as 'Rural' show preferences that group at the higher end of the continuum and peak at D1.7 (M=7.11, SD=3.71), and shows a steady incremental increase up to this point with the lowest preference choice at the lower end of the scale (D1.1 M=4.71, SD=3.40). This pattern of preference points towards a positive linear relationship between complexity and preference choice the opposite to the pattern seen for the urban sample.

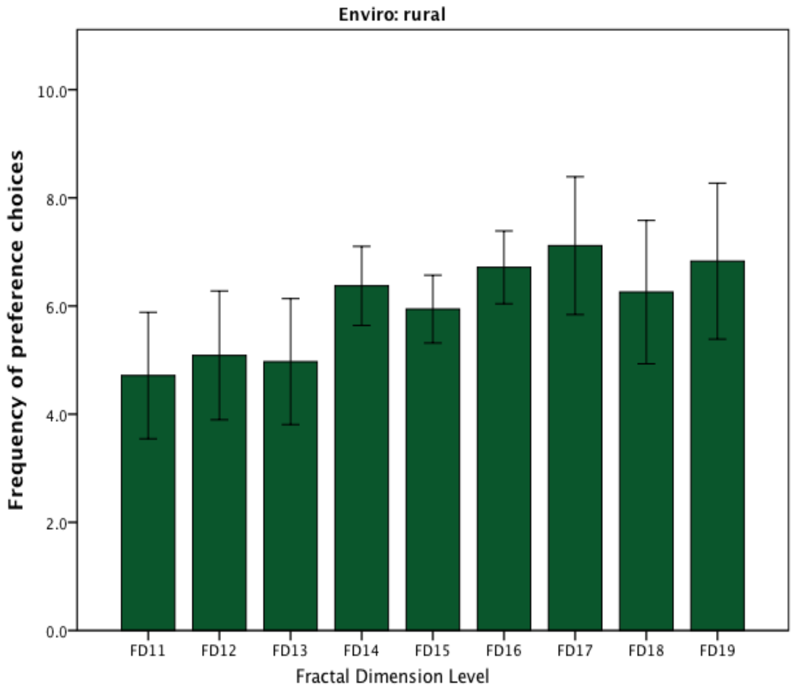


Figure 10.8- Bar Chart of preference choices across fractal scale in rural sample.

Suburban: As demonstrated in Figure 10.9, the participants identifying themselves as 'Suburban' show preferences that group at the mid-range of the fractal scale with the peak in preference at the mid point (both D1.5 M=7.10, SD=1.83; and D1.6 M=7.10, SD=2.10) offering some evidence to support the mid-range hypothesis of fractal preference. Preferences are lowest for the highest (D1.9, M=4.50, SD=3.62) and lowest (D1.1, M=5.65, SD=3.55) levels of fractal dimension in the scale. This pattern of preference points towards an Inverted-U relationship between complexity and preference choice.

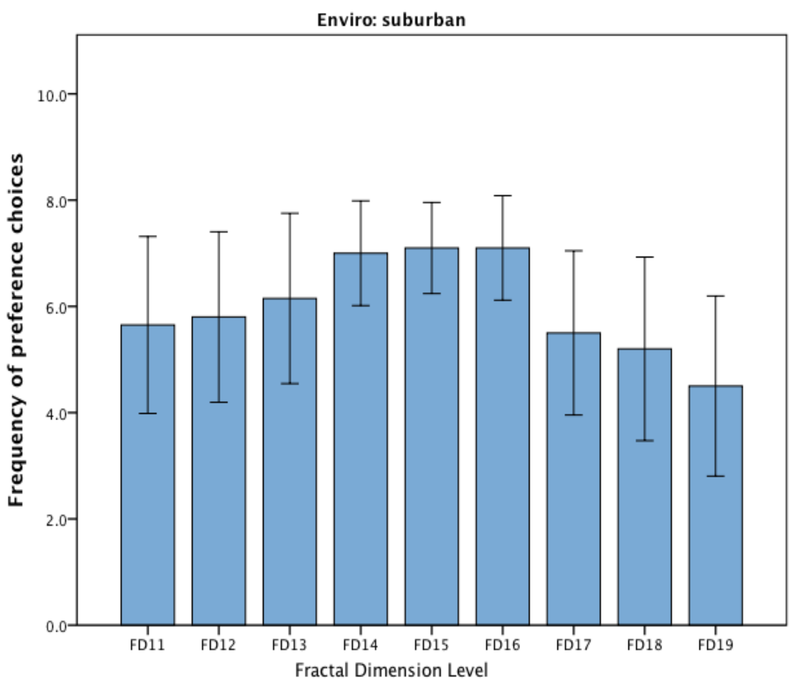


Figure 10.9- Bar Chart of preference choices across fractal scale in Suburban sample.

Further Inferential Statistics between Environmental Classification:

Repeated-measured ANOVA found that preference choices differ significantly between the different environmental classifications. Mauchly's test indicated that the assumption of sphericity had been violated, $\chi 2$ (35) = 728.07, p <0.001, the Greenhouse-Geisser adjustment was therefore applied ε=.196. The results found no significant difference across fractal level F (1.57, 117.75)=2.523 p=.097) however there was a significant interaction between fractal level and environmental classification F (3.14, 117.75)=3.97, p=.009). Post-hoc pairwise comparison found that significant differences between each environmental classification.

Table 10.1 Results of one-way ANOVA between environments

	Results of One-Way ANOVA
D1.1	F (2, 75)= 4.25, p=0.018
D1.2	F (2, 75)= 4.39, p=0.016
D1.3	F (2, 75)= 4.87, p=0.010
D1.4	F (2, 75)= .619, p=0.541
D1.5	F (2, 75)= 3.71, p=0.029

D1.6	F (2, 75)=. 990, p=0.377
D1.7	F (2, 75)= 4.63, p=0.013
D1.8	F (2, 75)= 2.78, p=0.069
D1.9	F (2, 75)= 4.75, p=0.011

Post-hoc Analysis: Following the significant difference across environmental group demonstrated in Table 10.1, post-hoc analysis was conducted across each fractal dimension level and the significant differences (Bonferroni adjustment for multiple comparisons) between environmental classifications. See Tables 10.2-10.10 for results of post-hoc analysis.

Table 10.2 pairwise comparisons between environments for D1.1 fractal stimulus

D1.1	Urban	Rural	Suburban
Urban		2.894*	1.959
Rural			-.936
Suburban			

Table 10.3 pairwise comparisons between environment for D1.2 fractal stimulus

D1.2	Urban	Rural	Suburban
Urban		2.827*	2.113
Rural			-.714
Suburban			

Table 10.4 pairwise comparisons between environment for D1.3 fractal stimulus

D1.3	Urban	Rural	Suburban
Urban		2.942*	1.763
Rural			-1.179
Suburban			

Table 10.5 pairwise comparisons between environment for D1.4 fractal stimulus

D1.4	Urban	Rural	Suburban
Urban		.194	-.435
Rural			-.629
Suburban			

Table 10.6 pairwise comparisons between environment for D1.5 fractal stimulus

D1.5	Urban	Rural	Suburban
Urban		.0571	-1.100
Rural			1.157*
Suburban			

Table 10.7 pairwise comparisons between environment for D1.6 fractal stimulus

D1.6	Urban	Rural	Suburban
Urban		-.409	-.796
Rural			-.386
Suburban			

Table 10.8 pairwise comparisons between environment for D1.7 fractal stimulus

D1.7	Urban	Rural	Suburban
Urban		-2.940*	-1.326
Rural			1.614
Suburban			

Table 10.9 pairwise comparisons between environment for D1.8 fractal stimulus

D1.8	Urban	Rural	Suburban
Urban		-2.431	-1.374
Rural			-1.057
Suburban			

Table 10.10 pairwise comparisons between environment for D1.9 fractal stimulus

D1.9	Urban	Rural	Suburban
Urban		3.133*	-.804
Rural			2.329
Suburban			

Summary:

The preliminary frequency analysis in this study also revealed that the significant differences in preference between environmental are present between the ‘urban’ and ‘rural’ sample therefore this comparison was included in the LME analysis and not comparison with the suburban sample. Although as acknowledged in previous studies within this thesis, the use of frequency data in 2A-FC designs has limitations, this initial analysis shows some interesting patterns of preference as a result of individual participant environmental classification. Further, more robust, analysis is required to explore the differences identified here in greater depth and this will be explored in the next section.

10.3.2 Linear-mixed effect modelling:

The study uses linear mixed-effect modelling. This method tested the fit of 3 models exploring preference for fractal patterns. Each model explored if and how well country (Egypt or UK), environmental classification (Urban or Rural), Gender and Age predict preferences for fractal images, either falling within Taylor's (2010) defined 'mid-range' peak preference point (D1.3-1.5), falling within a 'equalized mid' range which (D1.4-1.6) or the choice of the most complex image from each set (highest FD/lowest GIF score image). Both participant samples (participant ID) and stimulus display (Fractal patterns) were analysed as random effect. The model equations are outlined below:

- ***Model A-*** *(complexity ~ (country+enviro+gender+cAge)^2 + (1 | ID) + (1| display))*
- ***Model B*** -*(Taylor'sMidRange~ (country+enviro+gender+cAge)^2 + (1 | ID) + (1| display))*
- ***Model C-*** *(EqualizedMidRange~ (country+enviro+gender+cAge)^2 + (1 | ID) + (1| display))*

Model A- Complexity

complex ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 | display))

Model A explored the extent to which the variables Country, Environmental Classification, Gender and Age could predict the effect that the variables for the choice of the more complex images from a pair.

Overall fit of the model:

Analyses compared the variance explained by the fixed and random effects and explored the extent to which these variables explain the variance in the data. Model A (results shown in Table 10.11) is accounts for significantly more variance with fixed and random effects (AIC= 3227.6, df=13) than the null model with random effects alone (AIC= 3234.5, df=3), suggesting that the model is improved with the additional variables (χ^2 (10)= 26.884, p=0.003).

Table 10.11- Results from complexity model analysis

		β	SE	Z	Pr(>|z|)
Complexity hypothesis	Intercept	0.745	0.796	0.936	0.349
	Country (e-u)	-1.779	3.536	-0.503	0.615
	Enviro (u-r)	-2.965	1.105	-2.685	0.007**
	Gender (m-f)	-0.011	3.066	-0.004	0.997
	Age	-0.010	0.073	-0.139	0.889
	Country(e-u) x enviro (u-r)	1.275	1.062	1.202	0.229
	Country (e-u) x gender (m-f)	-0.815	1.152	-0.708	0.479
	Country (e-u) x Age	-0.100	0.351	-0.286	0.775
	Enviro (u-r) x Gender (m-f)	-2.226	1.109	-2.007	0.045*
	Enviro (u-r) x Age	-0.158	0.098	-1.612	0.107
	Gender (m-f) x Age	-0.068	0.295	-0.232	0.816

*Significance Codes: ***0.001, **0.01, *0.05.*

Additional goodness of fit analysis found that Age (χ^2 (4)= 7.9547, p=0.093), Country (χ^2 (4)= 2.6476, p=0.618) and Gender (χ^2 (4)= 7.2841, p=0.122) do not significantly add to the overall prediction of the model. Environmental classification was found to significantly improve the overall fit of the model (χ^2 (4)= 15.902, p=0.003).

Main Effects:

Environmental classification significantly influenced choice of complexity (β = -2.965, z = -2.685, p < 0.01) with rural participants having on average a 50% chance of choosing the complex image from the pair and the urban participants have an average of 6% chance of choosing the complex image from the pair (See Figure 10.10).

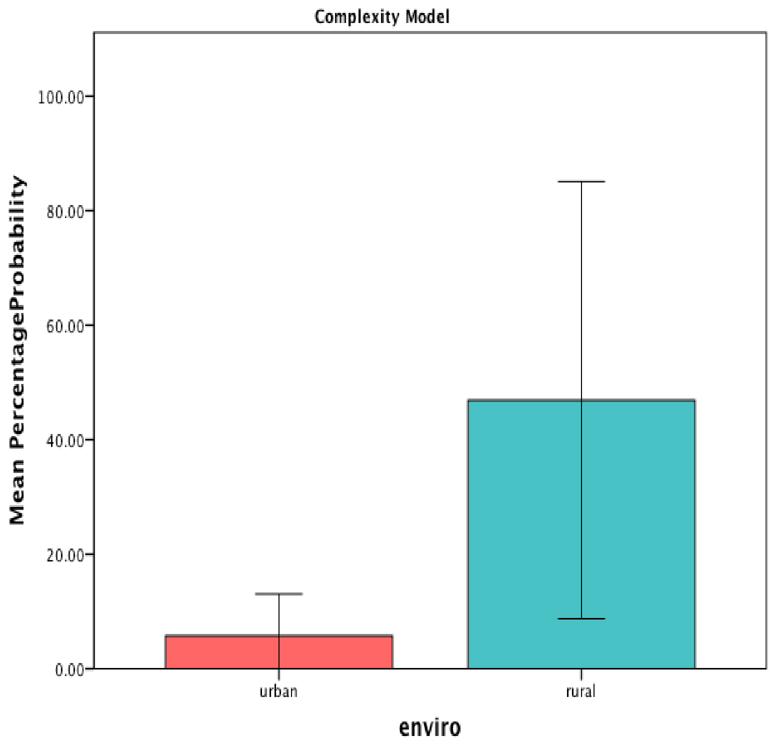


Figure 10.10 Bar Chart demonstrating differences Main effect of environment in Complexity Model

Interaction Effects:

In addition to the significant main effects of environment, the analysis shows a significant interaction between Environment and Gender (β = -2.226, z = -2.007, p = 0.045) (See Figure 10.11). Males in Urban environments have an average of

5.74% and Females in Urban environments have a 5.79%, Males in Rural environments have an average of 46.79% and Females in Rural 47.02%. Although relatively small across averaging, there is a different directional relationship between complexity choice and gender.

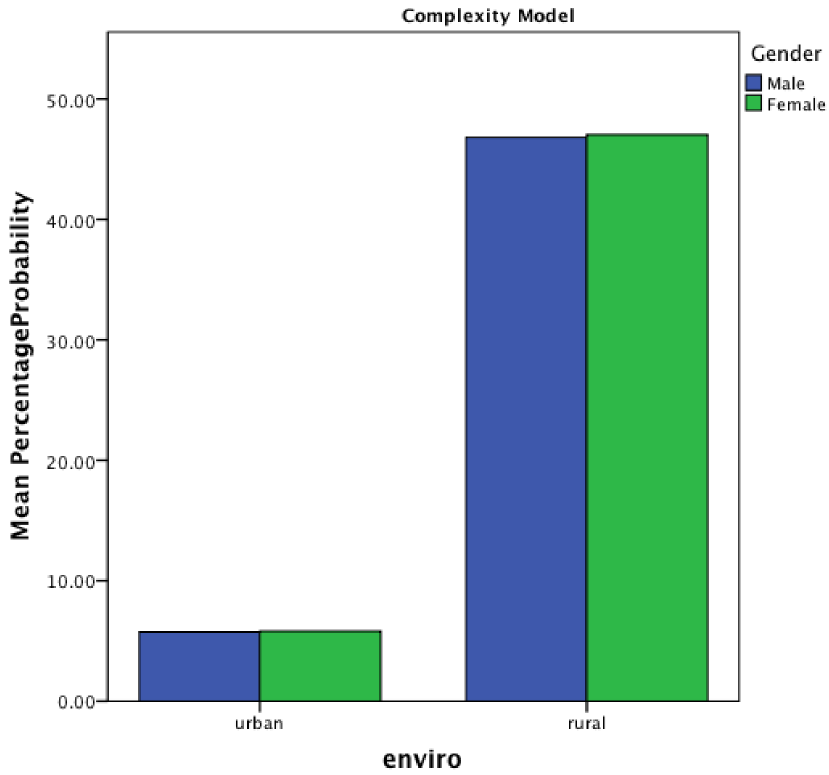


Figure 10.11 Bar Chart demonstrating interaction between enviro and Gender in Complexity Model

<u>Model B- Mid-Range</u>

$$MidRange \sim (country + enviro + gender + cAge)^\wedge 2 + (1 \mid ID) + (1 \mid display))$$

Model B explored the extent to which the variables country (UK – Egypt), environmental classification (Urban – Rural), Gender and Age could predict the effect that the variables for the choice of the mid-range image from a pair.

Overall fit of the model:

Analyses compared the variance explained by the fixed and random effects and explore the extent to which these variables explain the variance in the data. Model B is accounts for significantly (marginally) more variance with fixed and random effects (AIC= 2658.4, df=13) than the null model with random effects alone (AIC= 2656.6, df=3), suggesting that the model is improved with the additional variables (χ^2 (10)= 18.163, p=0.052).

Table 10.12- results from mid-range model analysis

		β	**SE**	**Z**	**Pr(>|z|)**
Mid-Range Hypothesis	Intercept	2.845	0.784	3.630	0.00028***
	Country (e-u)	-1.252	1.338	-0.936	0.349
	Enviro (u-r)	-0.790	0.404	-1.955	0.050
	Gender (m-f)	1.482	1.167	1.270	0.204
	Age	0.021	0.029	0.708	0.479
	Country(e-u) x enviro (u-r)	0.694	0.421	1.650	0.099
	Country (e-u) x gender (m-f)	-0.315	0.441	-0.715	0.474
	Country (e-u) x Age	-0.101	0.132	-0.767	0.443
	Enviro (u-r) x Gender (m-f)	-1.329	0.435	-3.057	0.002**
	Enviro (u-r) x Age	-0.051	0.036	-1.413	0.158
	Gender (m-f) x Age	0.095	0.112	0.852	0.394

*Significance Codes: ***0.001, **0.01, *0.05.*

Additional goodness of fit analysis found that Country (χ^2 (4)= 2.8553, p=0.582) and Age (χ^2 (4)= 14.372, p=0.549) do not significantly add to the overall prediction of the model. Gender (χ^2 (4)= 10.122, p<0.01) and Environmental Classification was found to significantly improve the overall fit of the model (χ^2 (4)= 7.2841, p<0.001).

Main Effects:

Environmental classification significantly influenced choice of mid-range (β = -0.790, z = -1.955, p = 0.050) with rural participants having around 94% of choosing the Mid-Range image from the pair and the urban participants have an 89% probability of choosing the Mid-Range image from the pair (See Figure 10.12).

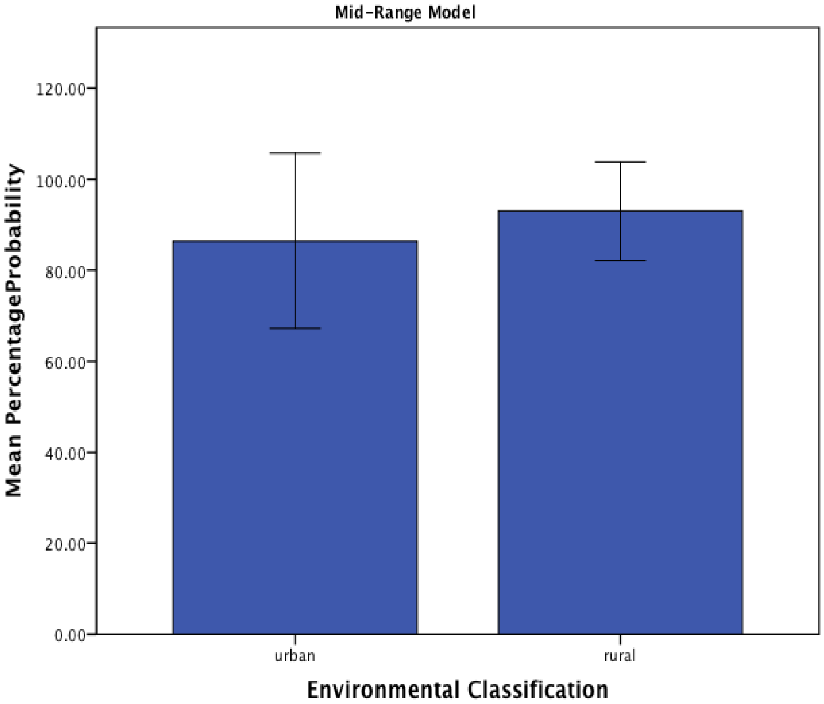


Figure 10.12- Bar Chart demonstrating differences Main effect of environment in Mid-range Model

Interaction Effects:

In addition to the significant main effects of environment, the analysis shows a significant interaction between Environment and Gender (β = -1.329, z = -2.007, p = 0.002). As demonstrated in Figure 10.13, the significant differences were found between males (93.96%) and females (78.85%) in the Urban sample and between males (97.96%) and females (88.80%) in the Rural sample.

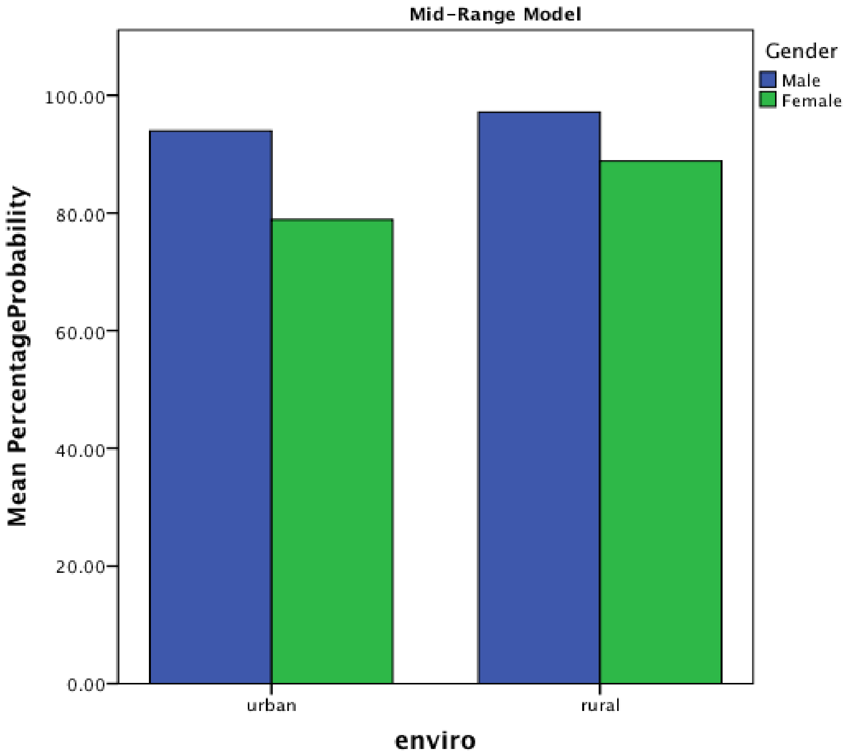


Figure 10.13- Bar Chart demonstrating interaction between of enviro and Gender in Mid-range Model

<u>Model C- Equalised Mid-Range</u>

Equalised Mid ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 | display))

Model C explored the extent to which the variables Country (UK – Egypt), Environmental Classification (Urban – Rural), Gender and Age could predict the effect that the variables for the choice of the more complex images from a pair.

Overall fit of the model:

Analyses compared the variance explained by the fixed and random effects and explore the extent to which these variables explain the variance in the data. Model C does not account for significantly more variance with fixed and random effects (AIC= 3330.6, df=13) than the null model with random effects alone (AIC= 3318.0, df=3), suggesting that the model is not improved with the additional variables (χ^2 (10)= 7.458, p=0.682). Additional goodness of fit analysis found each variable, Country (χ^2 (4)=2.127, p=0.712), Environmental Classification (χ^2 (4)= 4.389, p=0.356), Gender (χ^2 (4)= 3.116, p=0.539) or Age (χ^2 (4)=5.179, p=0.269) do not significantly add to the overall prediction of the model.

Table 10.13- results from equalised mid-range model analysis

		β	**SE**	**Z**	**Pr(>|z|)**
Equal-Mid-Range	Intercept	1.802	0.446	4.044	5.27e-05 ***
	Country (e-u)	-1.129	0.868	-1.301	0.193
	Enviro (u-r)	-0.233	0.268	-0.868	0.385
	Gender (m-f)	0.947	0.755	1.254	0.209
	Age	0.037	0.019	1.900	0.057
	Country(e-u) x enviro (u-r)	0.328	0.271	1.211	0.226
	Country (e-u) x gender (m-f)	-0.071	0.284	-0.250	0.803
	Country (e-u) x Age	-0.109	0.086	-1.267	0.205
	Enviro (u-r) x Gender (m-f)	--0.466	0.279	-1.665	0.096
	Enviro (u-r) x Age	-0.029	-1.245	-1.245	0.213
	Gender (m-f) x Age	0.069	0.957	0.957	0.338

*Significance Codes: ***0.001, **0.01, *0.05.*

The analysis found that none of the variables used in the analysis contributed to the fit of the model with the data, and based on this finding and the similarity between Model's B & C in early studies, the decision was made to discontinue the analysis in future studies within this thesis. This type of model has no support from literature and it has been shown there is no empirical evidence to suggest this model will no longer be used.

Despite the limitation with the model fit, the figure below (Figure 10.14) demonstrates no significant differences between country (β = -1.129, z = -0.868, p = 0.193) with UK participants having an average of 88.77% and Egyptian participants have a 72.63%.

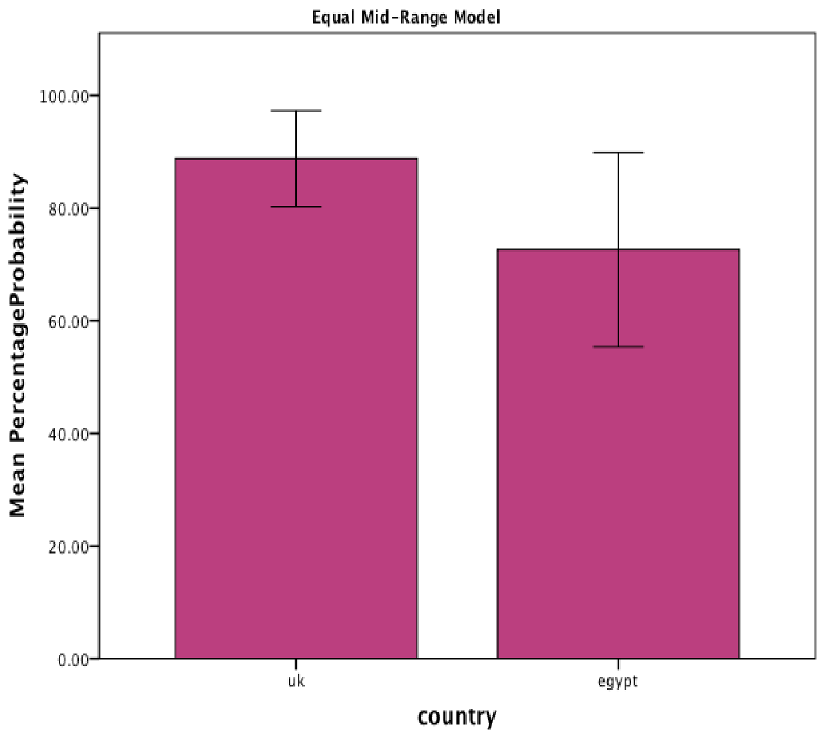


Figure 10.14 Bar Chart demonstrating main effect between country in EMR Model

There was also no significant difference between environmental classifications in (β = -0.223, z = -1.301, p = 0.385) with rural participants on average of 83.38% and urban participants 79.03%.

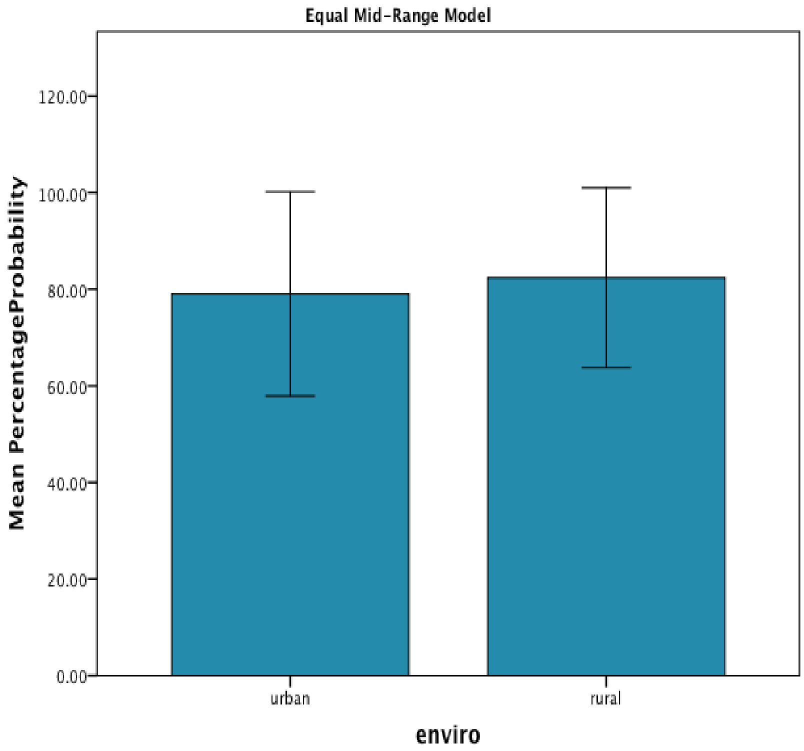


Figure 10.15 Bar Chart demonstrating main effect between environment in EMR Model

Overall Summary of Results:

The results of this study give some interesting insight into the individual differences involved in aesthetic evaluation of fractal images and the 'ideal' mapping or patterns of preference.

Initial analysis of the frequency data found significant differences in preference patterns as a result of environmental classification. This points to differences in preference shaped by micro-cultural (Environmental Classification) rather than macro-cultural (country). Looking at the overall patterns of preference we see no differences between country as both display more consistency across the FD levels. The frequency analysis shows differences in the direction of linear preference between gender. Males show highest preference for the lowest FD and lowest preference choices for highest FD whereas Females show the highest preference later in the fractal scale (D1.6) and the lowest FD value shows that lowest preference choices. Similar differences in patterns of preference are seen in environmental classifications. The Urban sample demonstrates a negative linear relationship with highest preference being shown for the lowest FD levels whereas the rural sample shows a positive linear relationship with the highest preference being shown for the highest FD levels. The suburban sample shows a much more traditional inverted-U shapes preference pattern.

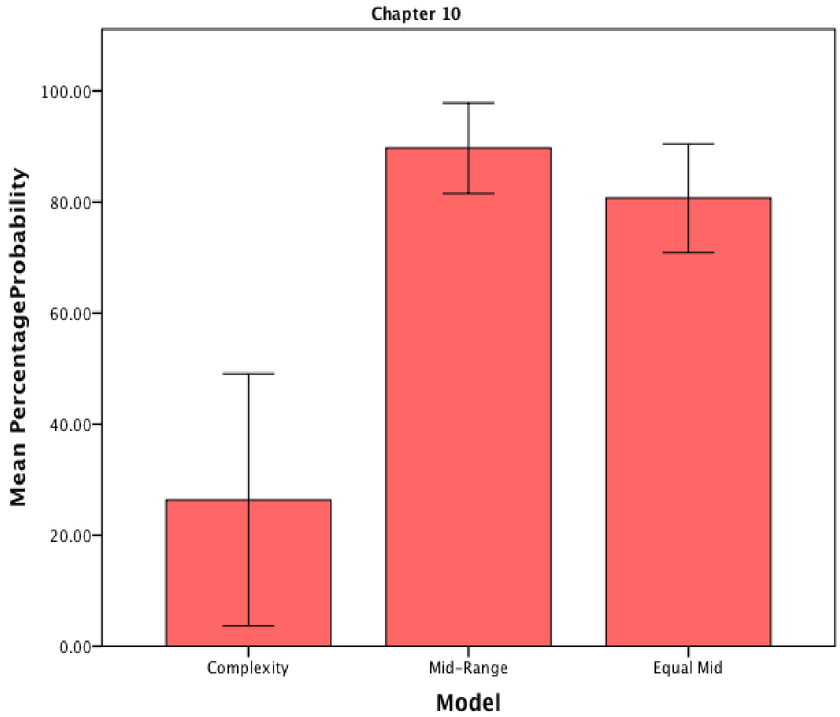


Figure 10.16 Averaged % of choosing images in each model

Model A (complexity); found that overall percentage choices are lower in the complexity model than in either of the mid-range models. Results of the model also demonstrate individual differences between participants as a result of environmental classification. Rural participants are more likely to choose a complex image from a pair than urban participants. Results also show that this main effect interacts with gender showing opposite gender effects in higher percentage for complexity. Model B (Taylor's Mid-Range) found marginally significant individual differences between urban and rural participants. Rural participants are more likely than urban participants to select a mid-range image from the pair. The model also found significant interactions between Environment and Gender; in both environmental groups Males are significantly more likely to choose the mid-range image from the pair. The fixed variables in Model C (Equalised Mid-Range) were unsuccessful in accounting for more variance than the random effect alone. The analysis found no significant differences as a result of environment, age, gender or country.

In summary, this study found that preference for fractal complexity differ significantly as a result of the individual differences environment and gender but not as a result of Country and Age.

10.4 Discussion

Results from the study show that individual differences play a role in predicting preference for fractal dimension. This finding offers evidence against the proposal that preference is universally 'set' at the mid-range of the fractal scale (Spehar et al., 2003). The findings instead suggest that individual variables such as environment and gender are strong predictors of preference for both fractal complexity and preferences falling within the mid-range.

Environmental differences:

Micro-cultural differences in environment emerge as strong predictors of preference for fractals in Model A & B where as macro-cultural difference (country) does not predict differences in preference. In Model A analysis, exploring complexity, the model found that rural dwellers are nearly 10 times more likely to choose the complex image from a pair than the urban dwellers. One possibility to understand this strong difference in preference could be that the urban participants generally experience less fractal complexity in their daily visual experiences and instead are more often repeatedly exposed to Euclidean geometry in man-made structures. The lack of familiarity with the complex fractal stimulus could result in a lack of fluency and difficulty of processing these shapes (Reber et al., 2004), which would result in lower aesthetic responses. The rural participants however are regularly exposed to fractal patterns in the natural environment. Fractal patterns can be seen in the trees, mountains, clouds, plants and more and this repeated exposure to fractal patterns could heighten the aesthetic response in the rural participants because of their familiarity with this type of pattern in their visual environment.

In Model B, the analysis explored the influence of the individual variables on the choice of the mid-range image in a pair. The results show that preferences differ as a result of environmental classification as also seen in the results of Model A. This difference is only marginally significant however rural dwellers are more likely to choose a mid-range image from a pair of stimulus than the urban dwellers. Analysis has shown that many of the natural objects we see in daily visual experiences display mid-range fractal properties that may account for the higher responses from rural participants. The difference between percentage choice however is smaller than in Model A, suggesting less variation in choice for fractal patterns at this level which would offer some support for the mid-rang hypothesis in which preference falls consistently between D1.3-1.5 as proposed by Taylor et al (2011).

Gender differences:

In addition to the individual difference between environmental classification and preference choice, both Model A and B found significant interactions between environmental classifications and gender. The complexity model found that in both rural and urban participants females had a higher percentage of choosing the most complex image suggesting perhaps that females have a higher threshold for preference for visual complexity. In the mid-range model, the percentage of choice for the mid-range fractal stimulus is higher in male participants from both the urban and rural samples. These results suggest that gender differences exist between complex and mid-range models and suggest an unusual function of gender on probability of preference choices for fractal images. Females appear to show higher preference for complexity and males a higher preference for mid-range images. These gender differences need to explore further and other studies within this thesis aim to take these questions forward.

Conclusions:

Overall the results from this study suggest that preferences for fractal and complex patterns are influenced by our direct visual experiences in the environment, whether participants self-classified the residential environment as ‘urban’ or ‘rural’. This finding is new to the field and lays the groundwork for potential wider interdisciplinary collaboration to explore the wider applications of understanding aesthetic responses to fractal patterns and by association the patterns of the natural world. It raises questions about the impact of the visual environment in which we spend time. The full implications and place in the literature will be explored in depth within the discussions chapter (Chapter 13).

11.0 - Connectedness to Nature & Environmental Classification

This exploratory study aimed to examine the impact that visual preferences (differing in environmental experience; rural or urban) have on how connected individuals feel to nature. Based on the strong dichotomous relationship previously found between Urban and Rural participants it was cautiously hypothesized that individual demonstrating higher preference for higher fractal patterns (from rural background) would score higher in how connected they feels with nature, as measured by the 'connectedness to nature' scale. These findings would suggest that basic 'bottom-up' visual processes influence our environmental attitude and thinking which would in turn have potential impact on behaviour. The study applied the research designs described in chapter 9 and 10 with the inclusion of an additional measure, the 'connectedness to nature' scale (CNS). Participants were recruited from Menoufia University, Egypt, as it was an exploratory study a total of 30 participants were in the sample. A Linear Mixed Effect Model A (Complexity) analysis demonstrated environment and age were significant predictors of preference for fractal patterns however connectedness to nature scale was not a significant predictor. The environmental effect was the opposite previous findings with urban participants showing higher preference for Complexity than rural participants. Results do not support the exploratory hypothesis that aesthetic preference for complex fractal patterns predicts connectedness to nature. It could be suggested that the connectedness to scale is perhaps not a valid cross-cultural tool; therefore future wider samples are needed to clarify the (potential) relationship.

11.1 Background/ Rationale:

The way individuals classify their environment is a significant predictor of preference for fractal patterns, those living in a rural environment are have a significantly higher probability of choosing the complex fractal images over individuals classifying themselves as urban dwellers (See Chapter 10). Previous literature have found that exposure to patterns and scenes impacts our preferences (Zajonc, 1968) and it is suggested that higher preferences were found for highly complexity fractal images in the environment because of the visual experiences. Those living in a rural environment are regularly exposed to a wide variety of fractal patterns and processes, whilst those living in urban environments have visual experiences mainly with man-made structures or features of the environment that display Euclidean rather than fractal geometric properties. The simplicity in form in Euclidean and man-made structures has been suggested as a major contributor in preferences for complex shapes as urban dwellers have shown a negative linear relationship with preferences falling incrementally as fractal complexity increases.

The differences found between aesthetic response and environmental classification led the researcher to consider the potential implication of the differences in preference. Is this aesthetic pattern implicit or explicit? This study aims to determine how related individuals feel to the natural environment and if this is a significant predictor for preference for fractal patterns. This study also lays the foundations of taking the investigation of fractals in an applied direction. It has been proposed that how connected one feel to nature will have a significant impact of behavioural response to the environment, such as sustainable and environmentally friendly behaviour, it has also been suggested that the increase of urban populations might mean that our connection with the natural environment is being lost. This study proposes that those living in rural environments will demonstrate higher connection to nature because of their increases exposure, and it will explore if connection to nature can be used to predictor preferences for fractal patterns (See chapter 5 for full review).

11.2 Methodology:

Participants: Participants were recruited from Menoufia University, Egypt, as it was an exploratory study a total of 30 participants were recruited. 15 females (Mean age=18.80 SD= 0.86) and 15 males (Mean age= 18.87, SD=0.83), from this sample 15 participants classified themselves as from 'Urban' environments, and 15 participants classified themselves as from 'Rural' environments.

Materials:

Stimulus: The study used the fractal pattern stimulus, for full details of stimulus selection and development see Chapter 6. See example of full set of images in Figure 11.1.

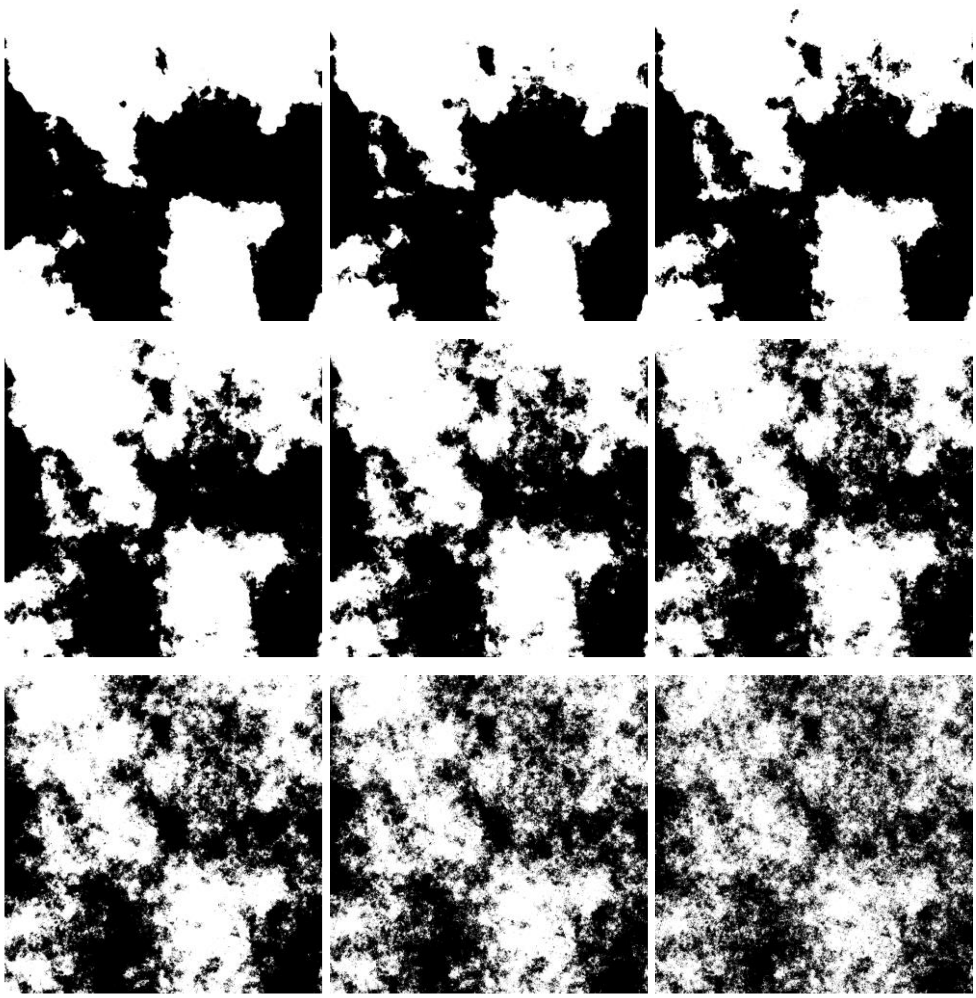


Figure 11.1- Example set of Fractal Stimulus showing progression D1.1-D1.9

Design: The study used a hard-copy 2A-FC survey design (see Figure 11.2). Participants were naïve independent sample with no previous experience taking part in previous studies within this thesis.

Which image do you like best? Tick on one to select it.

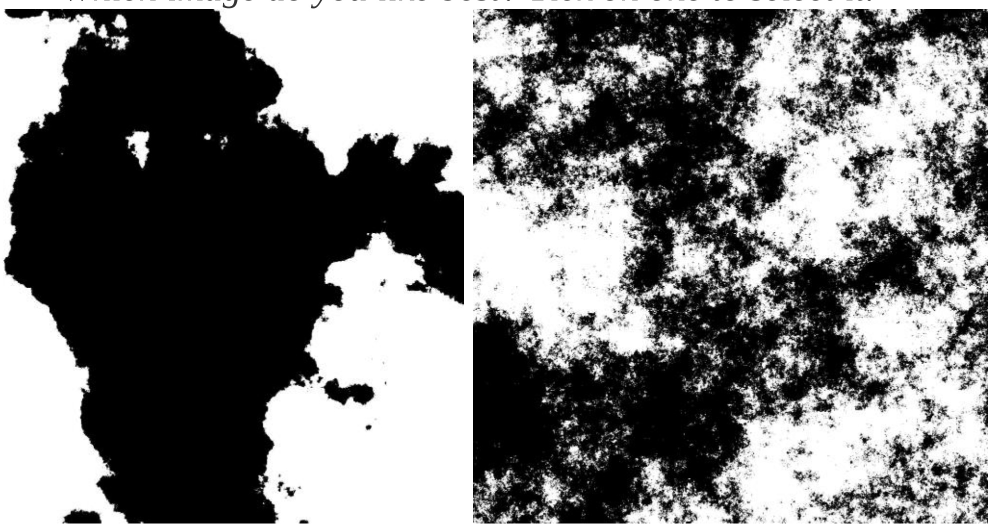


Figure 11.2 – example of 2A-FC task

Connectedness to Nature Scale (CNS):

Mayer & McPherson-Frantz (2004) developed the CNS tool for measuring an individual's affective relationship with the natural world and associated behaviour. The measure includes 14 statements. The CNS scale has high internal consistently, measures a one-dimensional construct and has demonstrated reliability with repeated testing. (Mayer & McPherson-Frantz, 2005)

Scoring the CNS:

Survey respondents rate a series of statements using a five-point likert scale to rate how strongly participants agree or disagree with each of the 14 statements (1 = strongly disagree & 5= strongly agree). Three questions are reversed scored (Questions 4, 12 & 14) and data was adjusted appropriately ahead of analysis. The maximum score possible is 70 demonstrating the highest-level connectedness to nature and the lowest possible score is 14 demonstrating the lowest level of connectedness with nature.

Procedure:

Participants were recruited within a department within Menoufia University, Egypt as an opportunity sample. Participants were asked if they would like to take part in a survey lasting approximately 15mins. After reading the information sheet and indicating consent by signing, they were asked to answer the 14 CNS statements, then asked to provide demographic details such as age, gender and environmental classification (with options reduced to 'urban' and 'rural' rather than the 4 options used previously). Then were asked to rate for 57 pairs, they image that they preferred. Following the 2A-FC task, participants were debriefed.

11.3 Results:

11.3.1 Patterns of Preference Analysis

Exploring first the patterns of preference in the sample by looking at the frequency data allows us to (tentatively) shows a linear relationship between fractal dimension and preference choice (see Figure 11.3). The graphing of the data allows us to see a clear separation between three groups of choice. The lower FD group (D1.1-D1.3) were preference peaks, the mid-range FD group (D1.4-D1.5) that preference is lower, then finally the higher FD group (D1.7-D1.9) in which preference has the lower frequency of choices.

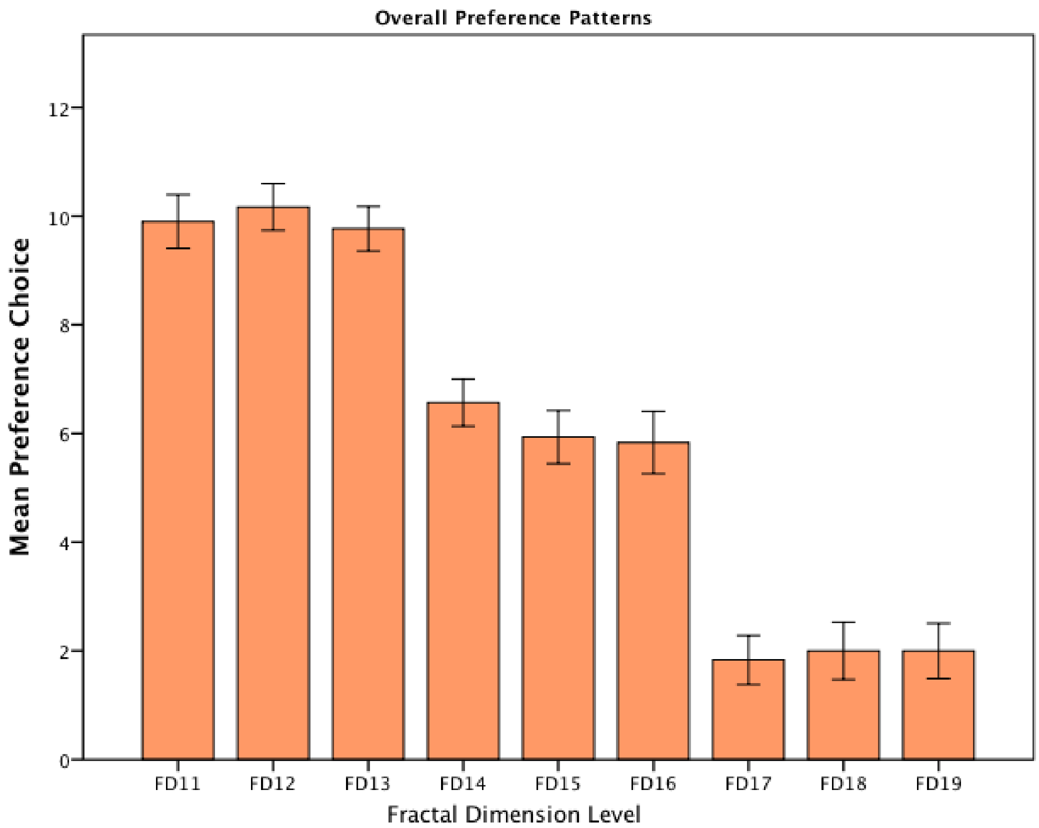


Figure 11.3 Bar Chart Representing Overall Preference Choices

Mauchly's test indicated that the assumption of sphericity had been violated, $\chi 2$ (35) = 455,639, $p < .001$, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .187$). The results show that there was a significant effect of fractal dimension, F (1.498, 73.422) = 31.074, $p < .001$, η2*p*=0.388. These results suggest that preference ratings differ significantly between each fractal dimension.

Following this analysis, post hoc pairwise comparisons were performed across the 9 different fractal dimensions to explore the point(s) at which these significant differences can be seen. Table 11.1 demonstrates the significant and non-significant relationships between each level, with the significant differences marked in orange and the non-significant differences marked in white. Analysis found significant differences of preference grouped mainly at the low-mid-high groupings discussed above. The overall analysis demonstrates that preference differs significantly as a function of fractal dimension and that preference within the sample differs most at the end of the Fractal Dimension scale.

Table 11.1 - Table of post-hoc differences for Entire Sample.

	D1.1	D1.2	D1.3	D1.4	D1.5	D1.6	D1.7	D1.8	D1.9
D1.1		-.420	-.180	1.760	2.240*	2.260*	5.260*	5.160*	5.160*
D1.2			.420	2.180*	2.660*	2.680*	5.680*	5.580*	5.580*
D1.3				1.940*	2.420*	2.440*	5.440*	5.340*	5.340*
D1.4					.480	.500	3.500*	3.400*	3.400*
D1.5						.020	3.020*	2.920*	2.920*
D1.6							3.000*	2.900*	2.900*
D1.7								-.100	-.100
D1.8									.000
D1.9									

* The mean difference is significant at the Adjustment for multiple comparisons: Bonferroni.

Environmental Classification:

Frequency analysis was explored across the environmental classifications in the group. Looking at Figures 11.4 and 11.5, both groups show highest preference choices for the lowest fractal dimensions in the stimulus. In both Rural and Urban groups preference peaks at D1.2 (Urban: M=8.65, SD=3.76; Rural: M=9.00, SD=2.60) however the lowest points differ with Urban groups preferring D1.8 stimulus least (M=3.23, SD=3.68) and the Rural group prefer D1.7 least (M=2.47, SD=2.29).

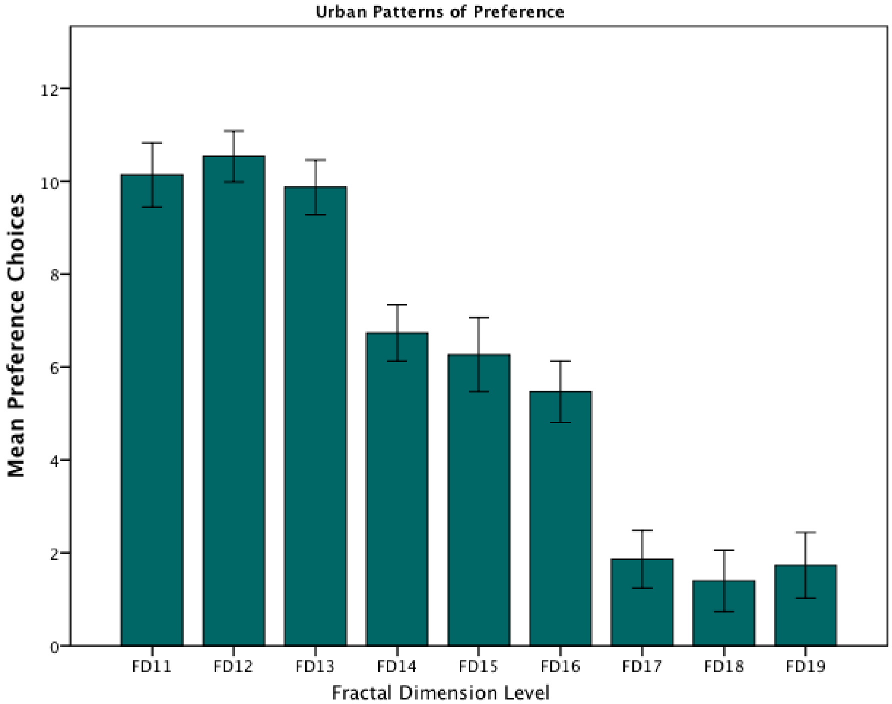


Figure 11.4 Bar Chart Representing Preference Choices in the Urban Group

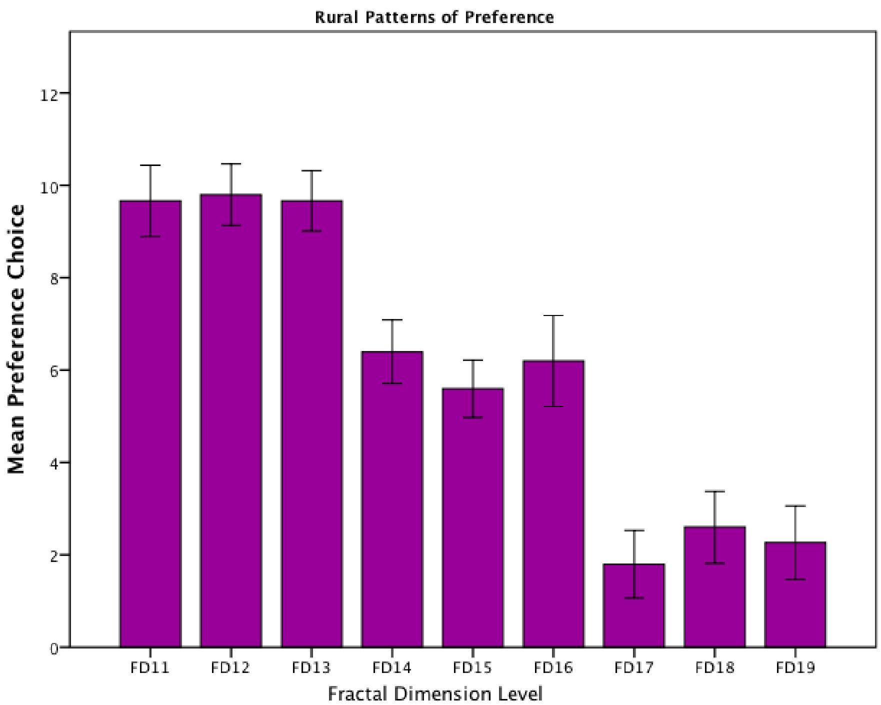


Figure 11.5 Bar Chart Representing Preference Choices in the Rural Group

Mauchly's test indicated that the assumption of sphericity had been violated, $\chi 2$ (35) = 450.720, $p < .001$, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .186$). The results show that there was no significant effect of fractal dimension, F (1.488, 71.401) = .433, p=.591, $\eta 2p$=0.009. These results suggest that fractal dimension ratings do not differ significantly between environmental classifications.

Connectedness-to-Nature Analysis:

Both Model A and B found no effect of connectedness-to-nature (CNS) scores and preference for fractal patterns.

Environmental Classification:

When looking at the overall mean scores between environmental classifications, analysis shows no significant difference in preference between environmental classification (*t* (28)=1.225, p=.231). Looking at the mean scores across groups we see, contrary to the hypothesis, urban dwellers scored higher in the CNS compared to their rural counterparts. These results suggest that those living in urban environments feel more connected than nature dwellers which contradicts many established findings within psychology and landscape research.

Table 11.2- Connectedness to Nature and environmental classification

	Connectedness to Nature Scale (Mean + SD)
Urban (N=15)	50.93 (7.36)
Rural (N=15)	47.13 (9.49)

Gender:

When exploring gender differences in CNS, analysis shows a non-significant difference between Males and Females (t (28)=1.84, p=.076), although not significantly differently different, males have on average scored higher than females in the CNS measure of how connected they feel to nature.

Table 11.3- Connectedness to Nature and gender

	Connectedness to Nature Scale (Mean + SD)
Male (N=15)	51.80 (6.43)
Female (N=15)	46.27 (9.71)

Age: When exploring Age differences in CNS, analysis shows a non-significant relationship between CNS and Age (r=.122, n= 50, p=.399).

11.3.2 Linear Mixed Effects Analysis

Model A- Complexity Preference:

Complexity ~ (cns + enviro + gender + cAge)^2 + (1 | ID) +   (1 | display))

Model A explored the extent to which the variables Connectedness to Nature, Environmental Classification (Urban – Rural), Gender and Age could predict the effect that the variables for the choice of the more complex images from a pair.

Overall fit of the model:

Analyses compared the variance explained by the fixed and random effects and explore the extent to which these variables explain the variance in the data (See Table 11.4). Model A does not account for significantly more variance with fixed and random effects (AIC= 1520.4, df=10) than the null model with random effects alone (AIC= 5880.9, df=3), suggesting that the model is not improved with the additional variables (χ^2 (10)= 4380.5, p<0.001).

Table 11.4 - Results from complexity model analysis

		β	SE	Z	Pr(>|z|)
Complexity hypothesis	Intercept	-6.048	8.043	-0.752	0.452
	CNS	0.189	0.174	1.087	0.277
	Enviro (u-r)	-8.189	3.144	-2.605	0.009**
	Gender (m-f)	1.314	2.346	0.560	0.575
	Age	-0.447	0.697	-0.642	0.521
	cns x enviro (u-r)	0.009	0.019	0.470	0.639
	cns x gender (m-f)	0.009	0.019	0.499	0.618
	Country (e-u) x Age	0.017	0.015	1.163	0.245
	Enviro (u-r) x Gender (m-f)	-0.095	0.325	-0.292	0.770
	Enviro (u-r) x Age	-0.659	0.253	-2.608	0.009**
	Gender (m-f) x Age	0.158	0.198	0.799	0.424

*Significance Codes: ***0.001, **0.01, *0.05.*

Additional goodness of fit analysis found that Connectedness to Nature (CNS) (χ^2 (4)= 4359.1, p<0.001) significantly improve the overall fit of the model and Environmental Classification (χ^2 (4)= 8.537, p=0.738) was marginally significant. Analysis found that Gender (χ^2 (4)= 1.818, p=0.769) and Age (χ^2 (4)= 7.265, p=0.122) do not significantly add to the overall prediction of the model.

Main Effects:

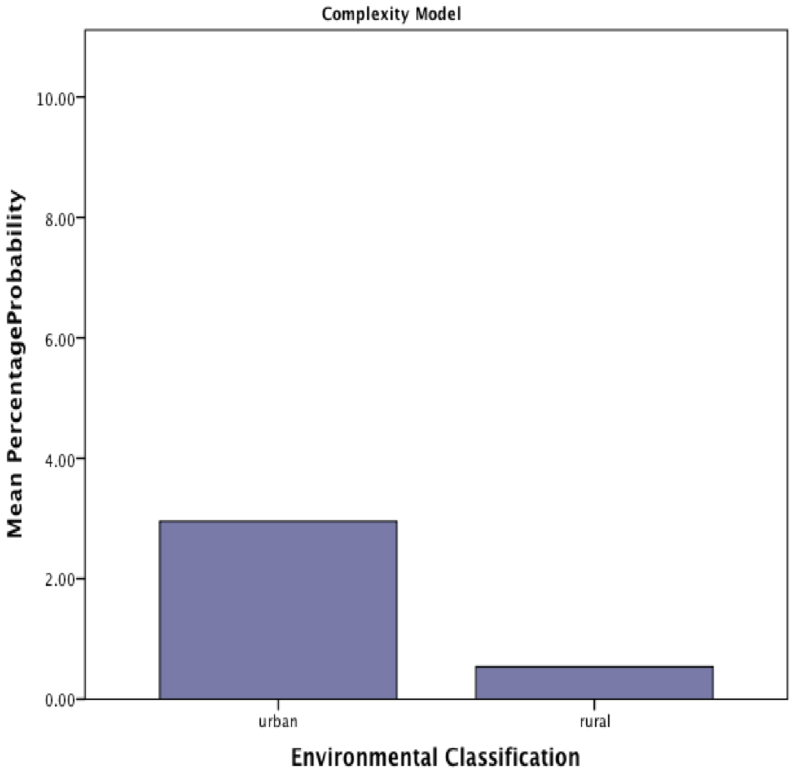


Figure 11.6 - Bar Chart of Main effect of environment in Complexity Model

Environmental classification was found to significantly influence choice of complexity (β = -8.189, z = -2.605, p <0.01) with rural participants having around less than 1% chance of choosing the complex image from the pair and the urban participants having around a 3% chance of choosing the complex image from the pair (See Figure 11.6).

Interaction Effects:

In addition to the significant main effects of environment, the analysis shows a significant interaction between Environment and Age (β = -0.659, z = -2.608, p <0.001). As demonstrated in Figure 11.7 in both the urban and rural participants preference for complexity decreases with age.

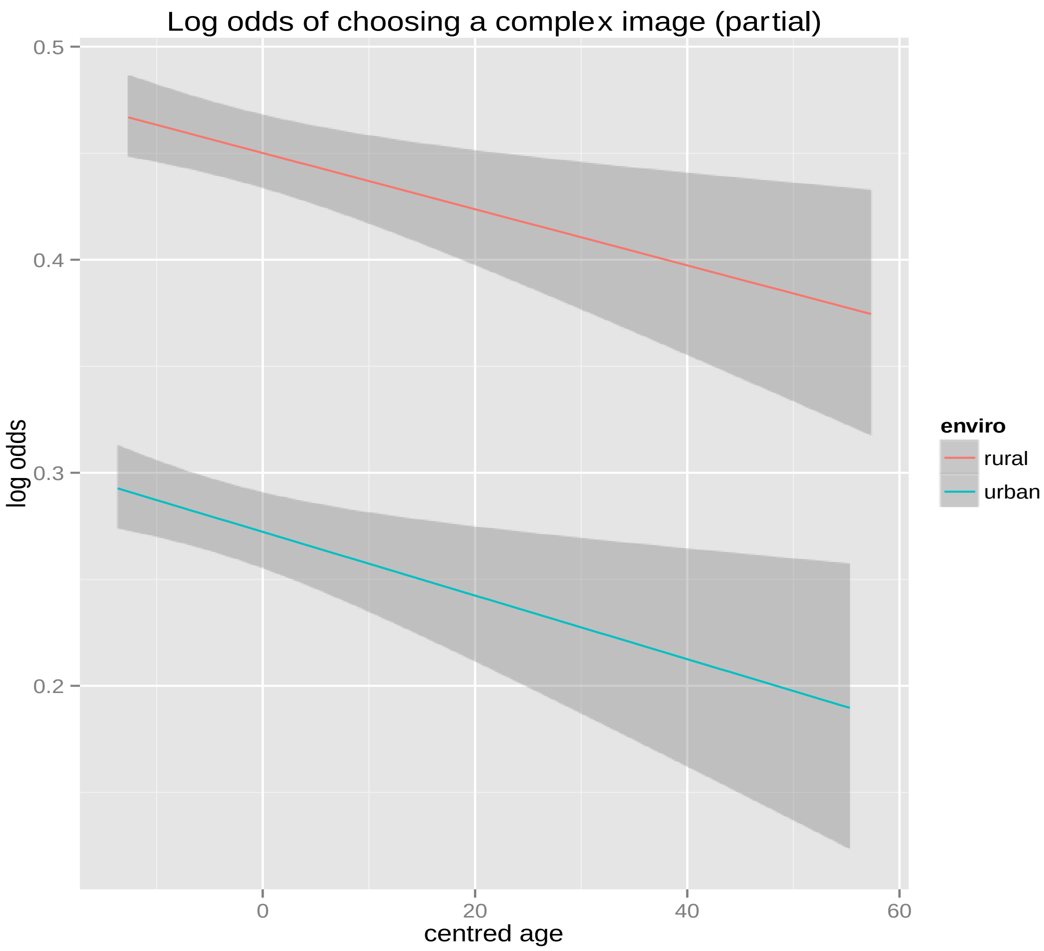


Figure 11.7 Interaction effect between Environment and Age in the Complexity Model

Model B - Mid-Range Preference

Mid-Range ~ (cns + enviro + gender + cAge)^2 + (1 | ID) +   (1 | display))

Model B explored the extent to which the variables Connectedness to Nature, Environmental Classification (Urban – Rural), Gender and Age could predict the effect that the variables for the choice of the mid-range images from a pair.

Overall fit of the model:

Analyses compared the variance explained by the fixed and random effects and explore the extent to which these variables explain the variance in the data (See Table 11.5). Model B does account for significantly more variance with fixed and random effects (AIC= 1319.3, df=13) than the null model with random effects alone (AIC= 4923.7 df=3), suggesting that the model is improved with the additional variables (χ^2 (10)= 3624.3, p<0.001).

Table 11.5- results from mid-range model analysis

		β	SE	Z	Pr(>|z|)
Mid-range hypothesis	Intercept	- 2.812	8.837	- 0.318	0.750
	CNS	0.115	0.191	0.602	0.547
	Enviro (u-r)	- 2.333	3.597	- 0.648	0.517
	Gender (m-f)	0.729	2.464	0.296	0.767
	Age	- 0.399	0.755	- 0.528	0.597
	cns x enviro (u-r)	0.002	0.020	0.118	0.906
	cns x gender (m-f)	0.001	0.021	0.044	0.965
	Country (e-u) x Age	0.009	0.016	0.605	0.545
	Enviro (u-r) x Gender (m-f)	0.241	0.342	0.704	0.481
	Enviro (u-r) x Age	- 0.168	0.289	- 0.581	0.561
	Gender (m-f) x Age	0.0870	0.208	0.419	0.676

*Significance Codes: ***0.001, **0.01, *0.05.*

Additional goodness of fit analysis found that Connectedness to Nature (CNS) (χ^2 (4)= 3606.1, p<0.001) significantly improves the overall fit of the model. Environmental Classification (χ^2 (4)= 1.389, p=0.846), Gender (χ^2 (4)= 1.229, p=0.873) and Age (χ^2 (4)= 0.848, p=0.932) do not significantly add to the overall prediction of the model.

Although there are no significant main or interaction identified within this model, some differences can be seen in percentage choice between the urban and rural groups with Rural participants having an approximately 8% percentage of making a mid-range fractal choice and Urban participants having a less than 1% (See Figure 11.8).

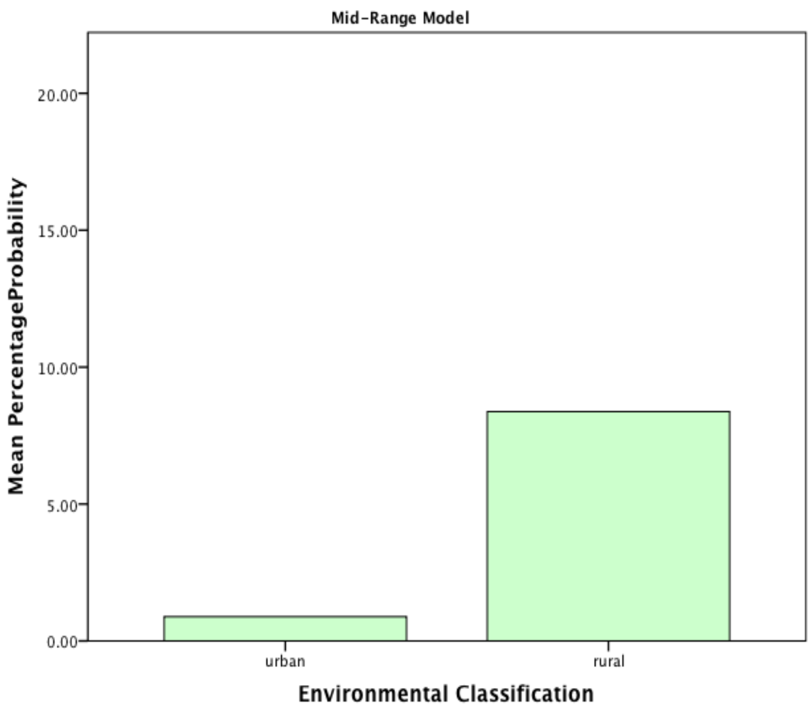


Figure 11.8 Bar Chart of Main effect in Environmental classification in Mid-Range Model.

Summary of Results:

The frequency analysis within this study found evidence of a negative linear relationship of preference and fractal dimension. Preference choice peaks at the lower end of the fractal scale and falls incrementally with increases in FD. When exploring if this patterns differs as a function of environmental classification evidence shows there is no significant effect of environmental classification on patterns of fractal preference and both groups demonstrate a negative linear pattern. Connectedness-to-nature mean scores were not found to differ significantly between environmental classifications, Gender or be significantly related to Age.

When conducting the linear-mixed effects modelling on the data Model A (complexity) was found to be no better at explaining the variance than the null model with random effects alone. The model found environmental classification to be a significant predictor of preference for the complex image from a pair with Urban participants having an approximately 3% choice of choosing the complexity image and Rural participants have a less than 1% choice. The model also found a significant interaction between Environmental Classification and Age with both Urban and Rural participants showing decreases in CNS with Age. Model B (Mid-Range) was found to be no better at explaining the variance than the null model with random effects alone. No significant main or interaction effects were seen in Model B. Although none significant, the rural group were more likely (approx. 8%) than the urban group (less than 1%). Results show that individual differences influence preference choices for fractal patterns although both Models were unsuccessful in accounting for more variance than the null models alone.

11.4 Discussion:

Results from the study show, in line with previous findings within this thesis, that individual differences play a role in predicting preference for fractal dimension. This finding offers an alternative position to the proposal that preference is universally 'set' at the mid-range of the fractal scale (Taylor et al, 2011; Spehar et al., 2003) as instead, a negative linear relationship between fractal dimension and preference choice was found within the sample. The findings suggest that individual variables such as environment and age are predictors of preference for both fractal complexity and fractal mid-range. Connectedness-to-Nature (CNS) scores however, were not a significant predictor to either complexity or mid-range models of fractal preference. There are several possible explanations for the lack of relationship between CNS and fractal preference, one could be that connection to nature is made up of a number of factors greater than 'environment classification', also previous literature has shown that feelings of connection with nature could be a result of a number of other experiences such as childhood experiences in nature and interests, hobbies or education all additionally shape preference for natural landscape/shapes and these that have not been considered or controlled for in the current study.

Environmental differences:

Model A (complexity) found self-reported environmental classification was a significant predictor of preference for differences fractal patterns. Unlike the previous results found within this thesis, rural participants are less likely (less than 1%) than urban participants (approx. 8%) to choose the complex image. In the findings discussed in Chapter 10 the opposite relationship was present with rural participants demonstrating a higher preference than urban participants, which was suggested to be a result of visual environmental exposure. The higher preference for complexity in the urban sample could be (although none significant) related to the Connectedness-to-nature (CNS) scores. In initial analyses conducted, the CNS was found to be higher in urban samples opposed to the previous literature, which would suggest the opposite difference should be found.

Age Differences:

Model A (complexity) also found significant interactions between environmental classification and age. The findings show that preference for complexity falls in both groups as Age increases. These findings are in line with previous literature that has found preference for complexity deceases as age increases. It has been suggested this may be related to survival and evolutionary foundations (Balling & Falk, 1982). The age range used in this study is limited and therefore to fully understand the impact of age on preference, a larger scale age range will be recruited to test this hypothesis further.

Limitations & Conclusions:

The results of this exploratory study should be taken cautiously, the sample was small (N=30) and recruited from Egypt solely, a sample which previous findings in this thesis suggest have a higher preference for lower fractal dimension patterns. Both models of preference do not account for more variance than the null models alone. The connectedness-to-nature tool is not a validated cross-cultural tool, and whilst all participants must have an ability to read in English to take part in the study. Comprehension of the questions may have been influenced by the taking part in the study in a second language.

Overall the findings of the current study show consistent findings with previous studies in this thesis, that environmental classification can significantly predict preference for fractal complexity. The rural and urban groupings however display the opposite direction, with urban populations showing preference higher preference for complexity than rural participants. Significant interactions were also found with the complexity model between environment and age, with preference for fractal complexity increasing in the rural sample with age and decreasing with age in the urban population. The results have no found significant interaction with the connectedness to nature scale, that results show that, within an Egyptian sample, how connected we feel to nature is not related to our aesthetic responses to it. Full discussion of the findings in relation to other results in this thesis and the literature will be can be found in Chapter 13.

12.0 The relationship between Lifespan, Culture & Gender as predictors to Fractal preference.

The study aimed to explore age as an additional predictor of preference for fractal patterns. Previous research within this thesis suggested that gender, culture, environment and age are significant predictors of preference for fractal patterns. The study uses a data set compiled from each 2A-FC study design within this thesis with the addition of a new small elderly sample to explore the strengths of the effects found in early studies. The study explores the patterns of preference in the entire data set as well as using 2 models, Model A preference for complexity and Model B, preference for mid-range to explore individual differences as predictors for this preference. The findings demonstrate support for the cross-cultural differences found previously, which have strengthened with larger sample sizes. Results also find a main effect of Gender on preference for complexity. Both models also found significant interactions with continent and gender. Age had neither a main or interaction effect on fractal preference. The results add support for the wider conclusions of the thesis, that individual differences account for preference for fractal patterns and this appears to be, in part, down to visual experience and in part down to gender.

12.1 Background/Rationale:

The current study uses a combination of the data sets collected as part of this thesis with the inclusion of an additional older aged sample to explore the impact of age found in previous chapters. Earlier studies in this thesis have also found culture as a strong predictor for preference for fractal patterns. The difference found across culture are supported by findings within the field of aesthetics and landscape design which suggest preference for fractal patterns is a function of visual experience. Continental differences have been used to classify the large and varied sample within the thesis, and these have offered a good insight into similarities and differences across culture as such

Several studies within this thesis have found strong gender differences in preferences for fractal patterns. Previous results show mixed findings for both the complex and the mid-range models, however significant main and interactions of gender have been found in different data sets. It could be suggested that innate perceptual differences between male and females in aesthetic processing could account for the differences found in preference and this study aims to explore this further.

Age has been found to be a significant predictor of preference in a number of previous studies within this thesis. To explore these findings further, an additional age set including older people was added to the data to allow a lifespan age range to be used to explore the stability of preference for fractal complexity as a function of age and gender.

Whilst one of the strongest predictors of preferences found within this thesis was environmental classification, with significant differences between Urban and Rural dwellers, as this was a consideration in later studies of this thesis based on earlier findings not all data sets include this information therefore it was decided this factor was not included within the analysis.

12.2 Methodology:

All 2A-FC data sets from this thesis were combined to further explore the strengths of findings in previous analyses, which found Culture, Gender and Age and their interactions as significant predictors of preference for fractal patterns.

Participants:

In total the sample size was 443 participants, including 228 males and 204 females made up from the participants from studies 9, 10 & 11 with the addition of elderly samples recruited from local day centres. The mean age of participants was 31.03 (SD=14.45); with age ranging from a min age 17 years and a maximum age 88 years. Participants were recruited using a variety of methods including opportunity, online and targeted recruitment. To collect the older sample, the researcher visited a number of day centres, data at these environments were collected using hard copies to facilitate uptake of older participants.

Procedures:

Participants were recruited using a mixed of online and hard copy survey methods from a variety of locations including universities, online participant sample pools and day centres. Ahead of the study participants were provided an information sheet and also given the opportunity (both verbally in day-centre cases and online in other data collection methods) to ask questions. Following this consent was requested and all participants were asked to provide demographic information including Age, Gender, country of residence and environmental classification. The study involved participants making preference choices from 57 paired fractal images (for example stimulus set see Figure 12.1). When presented with each pair participants were asked ‘which they liked best’, for example of methodology see Figure 12.2

Materials:

Stimulus: The study used the fractal pattern stimulus as discussed in the methodology section of this thesis. For full details on development and selection please see Chapter 6.

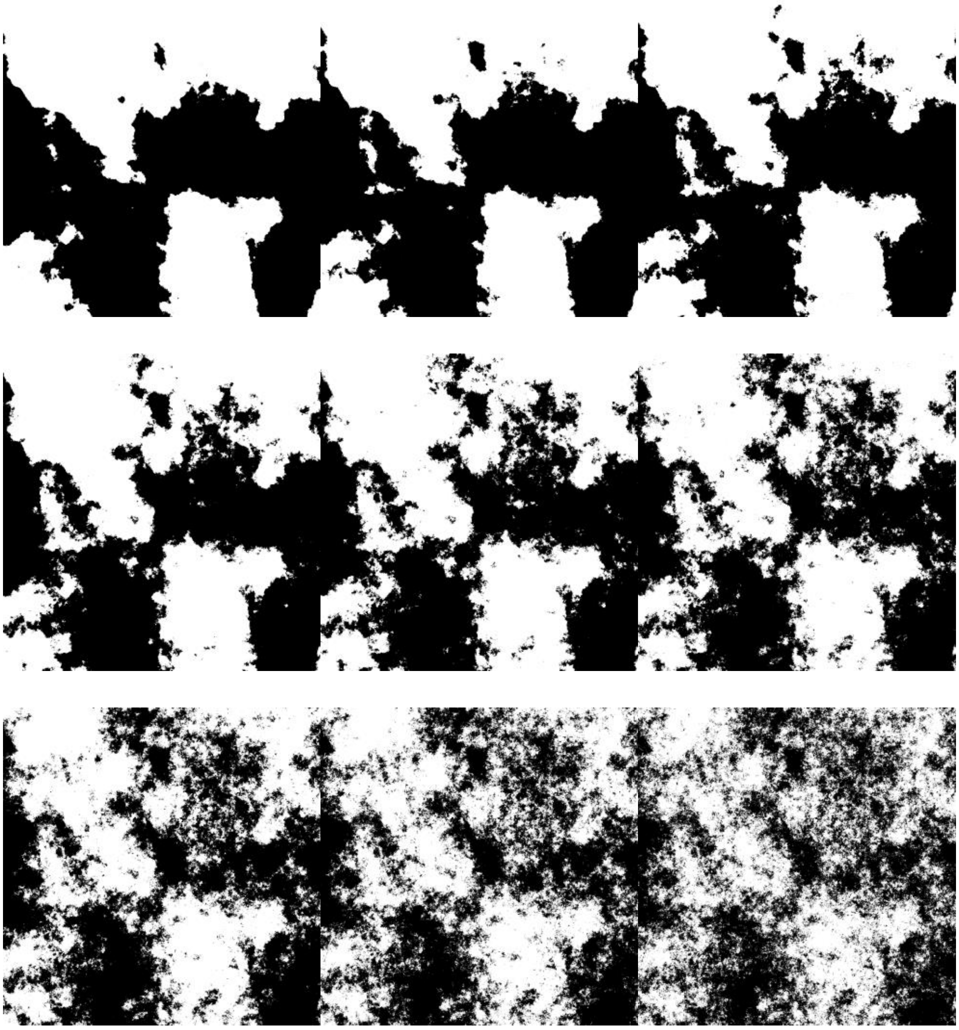


Figure 12.1- Example set of Fractal Stimulus showing progression D1.1-D1.9

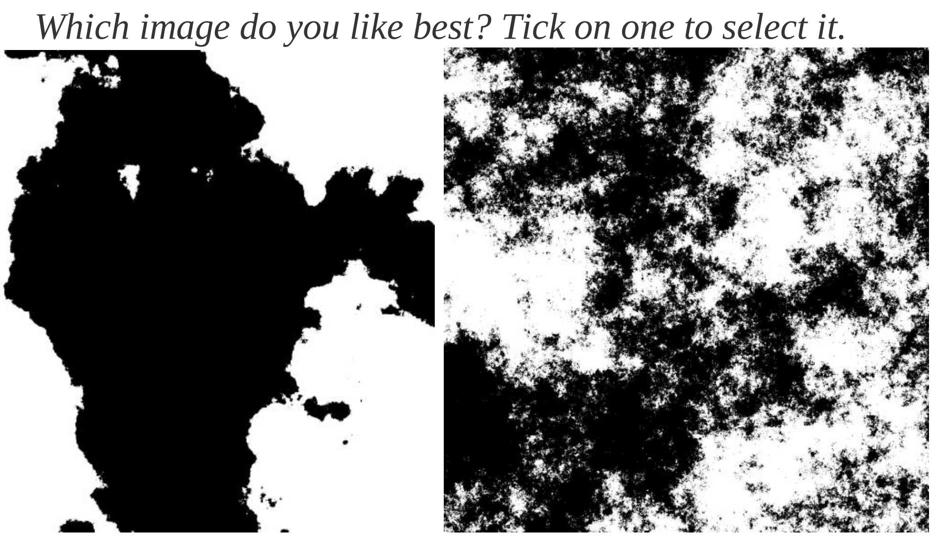


Figure 12.2 – example of 2A-FC task

12.3 Results:

12.3.1 Patterns of Preference Analysis

Initial analysis involved exploring the overall patterns of preference in the sample by looking at the frequency data. This data indicates a peak of preference at D1.2 (M=6.889, SD=3.898) and preference choices lowest at D1.8 (M=4.69, SD=3.89). As demonstrated in Figure 12.3, preference is peaks and is grouped at the low-to-mid-range of the fractal scale and begins to fall at the higher end of the fractal scale.

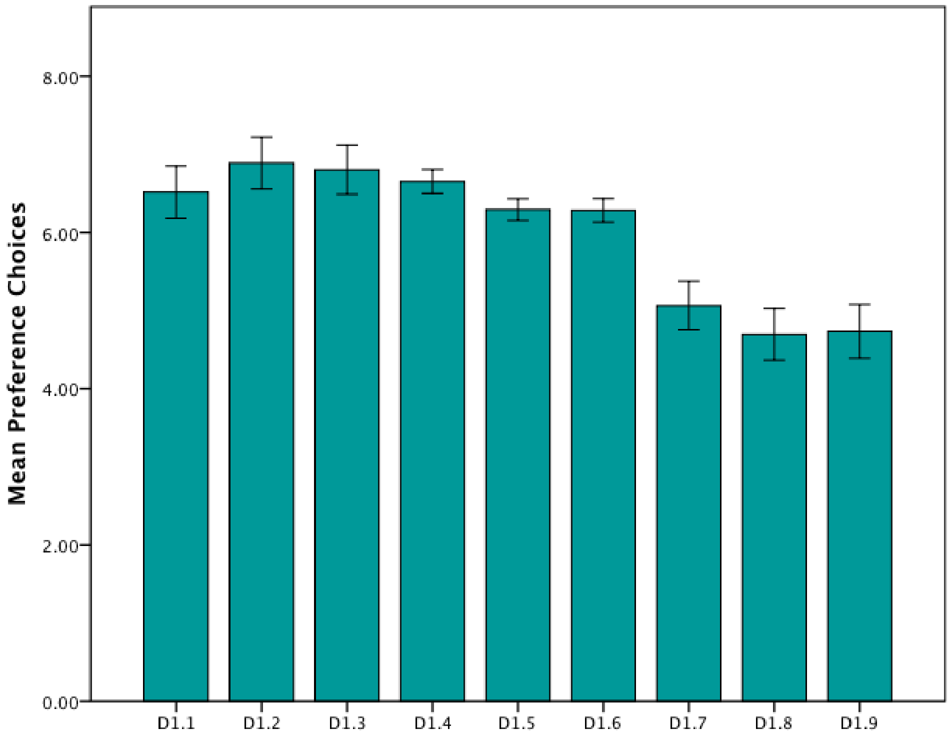


Figure 12. 3 Bar Chart of Overall Fractal Dimension for sample

Mauchly's test indicated that the assumption of sphericity had been violated, ($\chi 2$ (35) = 5518.759, p < .001); therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ε = .183). The results show that there was a significant effect of fractal dimension, F (1.467, 777.458) = 35.061, p < .001, $\eta 2p$=0.062. These results suggest that preference ratings differ significantly between each fractal dimension.

Following this analysis, post hoc pairwise comparisons were performed across the 9 different fractal dimensions to explore the point(s) at which these significant differences can be seen. Table 12.1 demonstrates the significant and non-significant relationships between each fractal level, with the significant differences marked in orange and the non-significant differences marked in white. Analysis found significant differences of preference grouped mainly at the high points of the fractal scale consistent with the patterns seen in Figure 12.3. The overall analysis demonstrates that preference differs significantly as a function of fractal dimension and that preference demonstrates the most variance the higher end of the Fractal Dimension scale.

Table 12.1: Table of post-hoc differences for Entire Sample.

	D1.1	D1.2	D1.3	D1.4	D1.5	D1.6	D1.7	D1.8	D1.9
D1.1		-.373*	-.286*	-.137	.224	.224	1.452*	1.819*	1.782*
D1.2			.087	.235	.597	.606	1.825*	2.192*	2.154*
D1.3				.149	.510	.520	1.738*	2.105*	2.068*
D1.4					.362*	.371*	1.589*	1.957*	1.919*
D1.5						.009	1.228*	1.595*	1.557*
D1.6							1.218*	1.586*	1.548*
D1.7								.367*	.330*
D1.8									-.038
D1.9									

* The mean difference is significant at the Adjustment for multiple comparisons: Bonferroni.

Location Differences:

Frequency data explored the differences between grouped locations. Figures 12.4 - 12.7 below show the differences in preference patterns across the location groups used in the study. The European (Figure 12.4) sample shows highest preference at the low-to-mid range with less frequency of choice at the higher end of the fractal scale. The North American sample (Figure 12.5) shows the opposite pattern of preference with less preference choice for the lower FD images and increases in choice with increases in fractal dimension. Both Central Asian sample (Figure 12.6) and African sample (Figure 12.7) show similar patterns of preference, peaking at the low-to-mid end of the fractal scale.

Table 12.2 Participant numbers in each location group

	Participant Numbers (N)
Europe	**177**
North America	**24**
Central Asia	**195**
Africa	**97**

Mauchly's test indicated that the assumption of sphericity had been violated, ($\chi 2$ (35) = 4995.552, p < .001); therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ε = .184). The results show that there was a significant effect of fractal dimension and location grouping (F (4.421, 720.6) = 3.995, p < .001, $\eta 2p$=0.024). These results suggest that preference ratings differ significantly between fractal dimension and location grouping however post-hoc analysis found no direct differences across the groups.

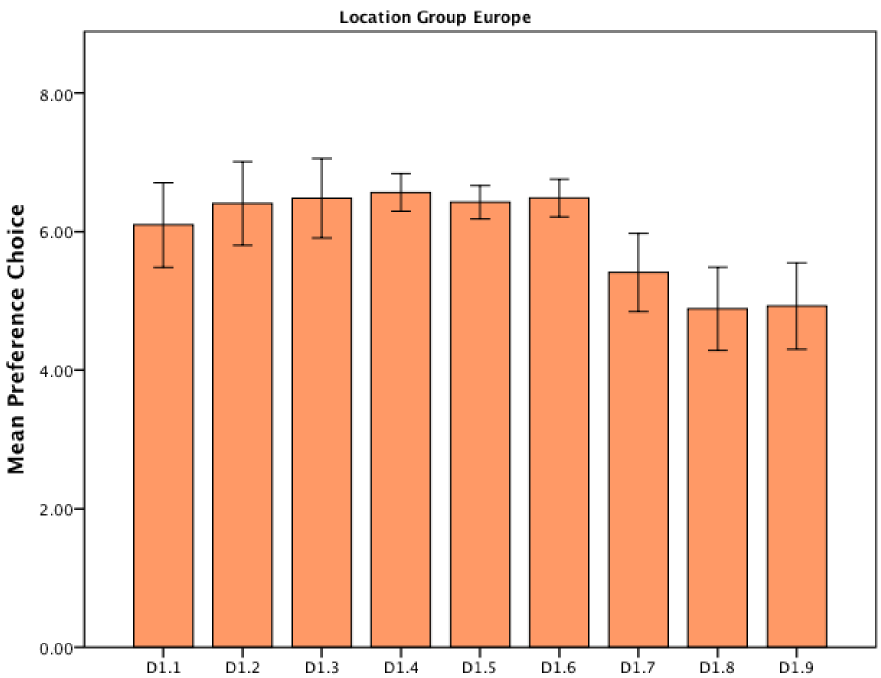


Figure 12.4 - Bar Chart of Overall Fractal Dimension for European sample

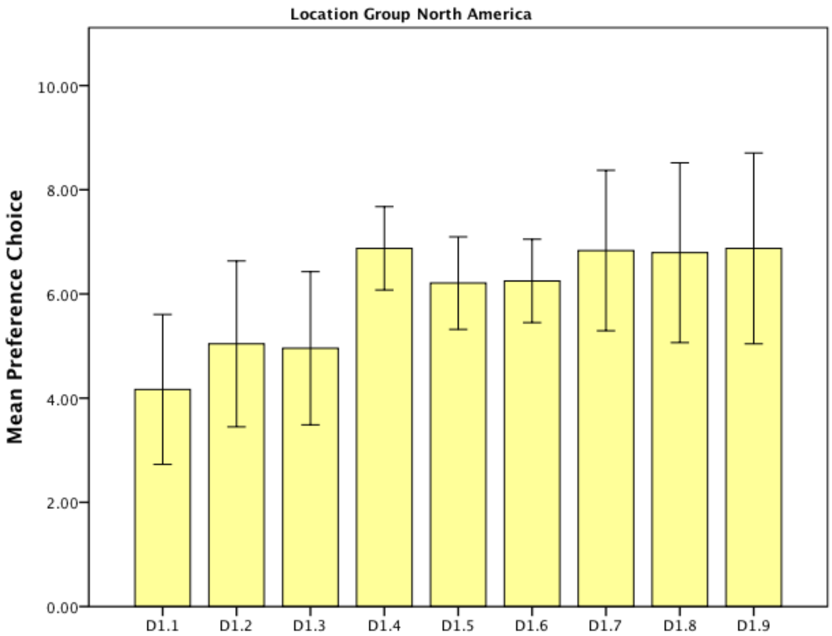


Figure 12. 5 Bar Chart of Overall Fractal Dimension for North American sample

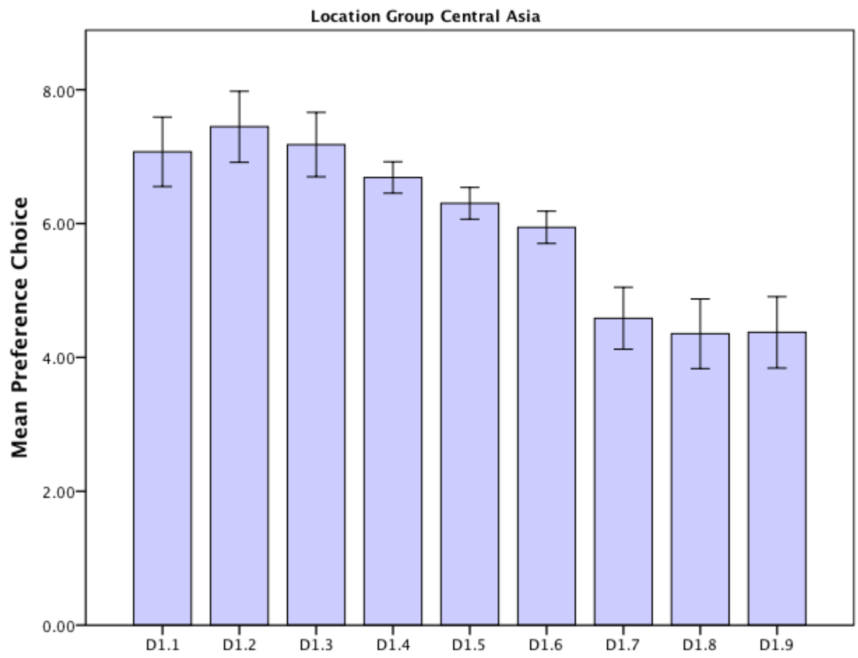


Figure 12. 6 Bar Chart of Overall Fractal Dimension for Central Asian sample

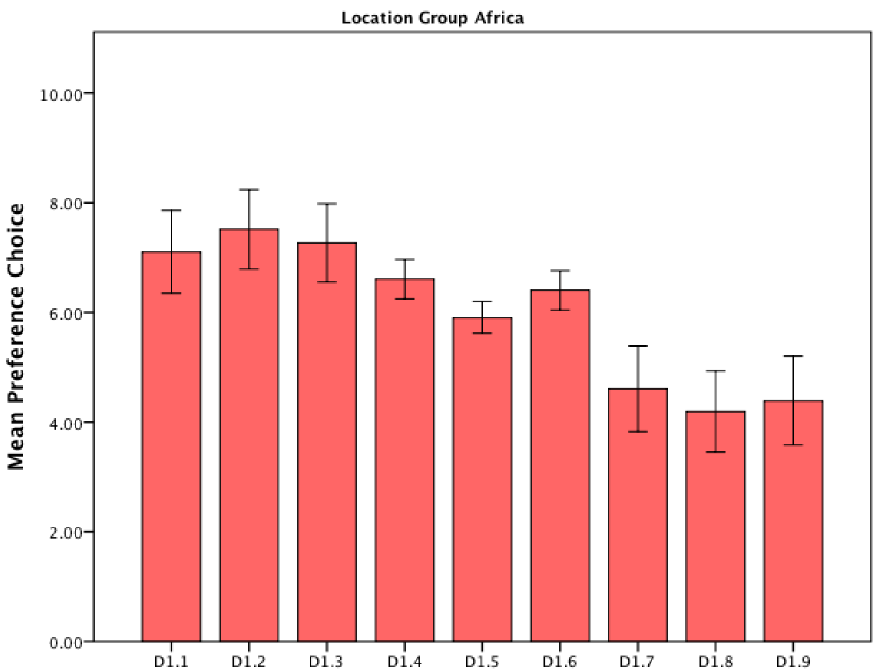


Figure 12. 7 Bar Chart of Overall Fractal Dimension for African sample

Gender:

As Gender has emerged as a significant predictor of fractal preference from previous analysis within this thesis, the frequency preference patterns of fractal dimension were explored across gender ahead of the linear-mixed effects modelling. In the male sample preference peaks at D1.2 (M=7.32, SD=3.94) and continues to fall as fractal dimension increases from this point. The patterns of preference for male participants (see Figure 12.8) point towards a low-to-mid peak in preference for fractal complexity.

The female sample shows a different pattern of preference across the fractal scale (See Figure 12.9). Preference for the Female sample peaks at D1.6 (M=6.58, SD=1.88) and there is less variation across each fractal dimension than male participants. This lack of clear variance across scales means there is no clear directional or curvilinear pattern emerging from the frequency data for the female sample.

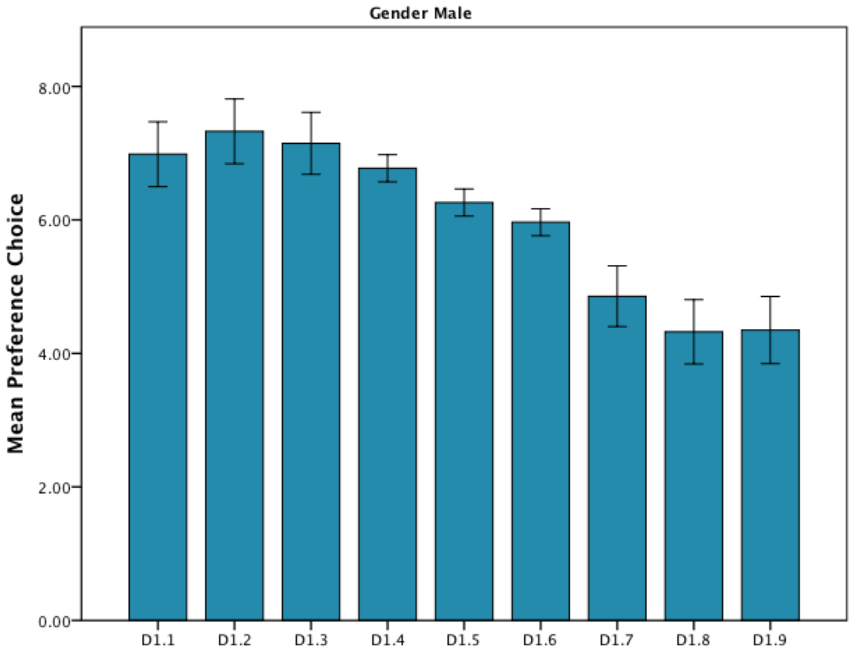


Figure 12. 8 Bar Chart of Overall Fractal Dimension for Male sample

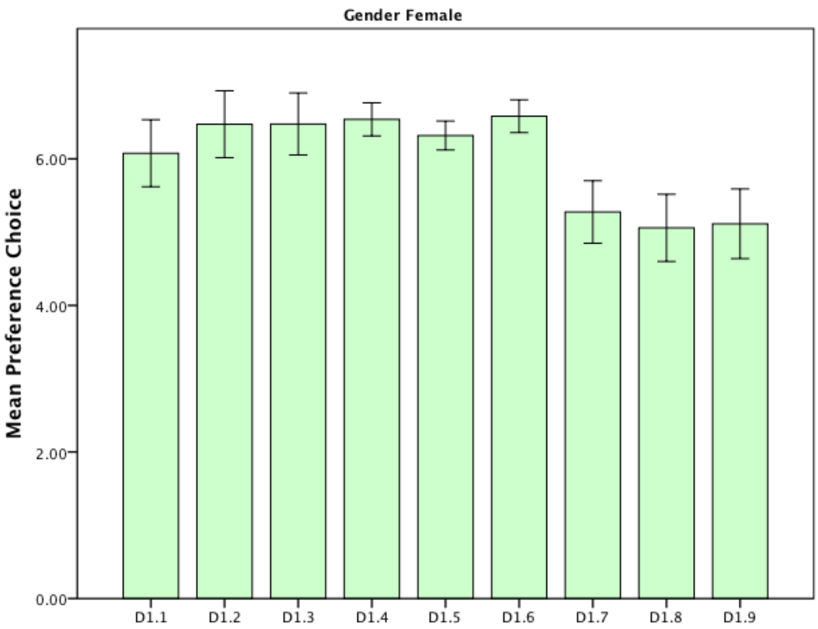


Figure 12. 9 Bar Chart of Overall Fractal Dimension for Female sample

12.3.2 Linear Mixed Effects Analysis

Model A- Complexity

complex ~ (continent + gender + cAge)^2 + (1 | ID) + (1 | display)

Model A explored the extent to which the variables Continent, Gender and Age could predict choice of the more complex (higher FD) fractal image from a pair, Table 12.3 shows the main findings.

Table 12.3- Results from complexity model analysis

		β	SE	Z	Pr(>|z|)
Complexity hypothesis	Intercept	-0.631	0.244	-2.583	0.00978 **
	continent.a-e	-0.356	0.665	-0.535	0.59252
	continent.c-e	-2.261	0.273	-8.267	< 2e-16 ***
	continent.n-e	-1.311	0.504	-2.601	0.00930 **
	gender.M-F	-1.585	0.328	-4.827	1.38e-06 ***
	cAge	-0.007	0.008	-0.940	0.34701
	continent.a-e:gender.M-F	1.446	0.549	2.636	0.00839 **
	continent.c-e:gender.M-F	1.703	0.406	4.195	2.73e-05 ***
	continent.n-e:gender.M-F	0.877	0.704	1.246	0.21263
	continent.a-e:cAge	0.003	0.052	0.051	0.95965
	continent.c-e:cAge	-0.001	0.016	-0.011	0.99099
	continent.n-e:cAge	-0.007	0.023	-0.282	0.77820
	gender.M-F:cAge	0.028	0.013	2.096	0.03606 *

*Significance Codes: ***0.001, **0.01, *0.05.*

Overall fit of the model:

Analyses compared the variance explained by the fixed and random effects and explore the extent to which these variables explain the variance in the data. Model A accounts for significantly more variance with fixed and random effects (AIC= 17040, df=21) than the null model with random effects alone (AIC= 17154, df=3), suggesting that the model is improved with the additional variables (χ^2 (18)= 125.14, p<0.001).

Additional goodness of fit analysis found that Continent (χ^2 (15)= 99.06, p<0.001) and Gender (χ^2 (7)= 29.29, p<0.001) significantly improves the overall fit of the model however Age (χ^2 (7)= 6.845, p=0.445) does not significantly add to the overall prediction of the model.

Main Effects:

Results of the model identify significant main effect of continent. European participants show an average 22% choice of the complex image from a pair, analysis show this did not differ significantly from African sample (β = -0.356, z = -0.535, p =0.592), which showed an average choice of approximately 17% choice. Significant differences were however found between Europe (22%) and North American (8%) (β = -1.311, z =-2.601, p <0.01) and Europe (22%) and Central Asia (3%) (β = -2.261, z =-8.267, p <0.001) suggesting individual difference in preference across location. See Figure 12.10 for a comparison of percentage choice across each continent.

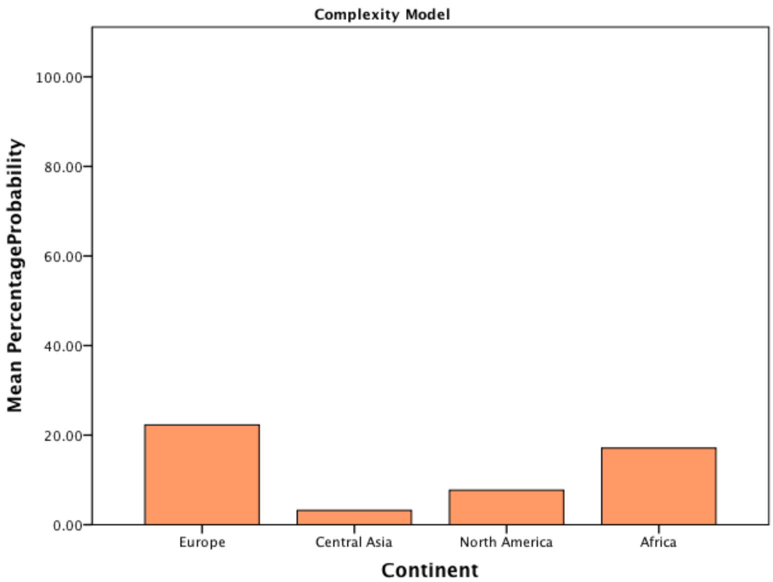


Figure 12.10 - Bar Chart of % choice of complex image from a pair across continent

In addition the model found a main effect of gender on preference for fractal complexity. As demonstrated in Figure 12.11, females show a significant increased choice in complex fractal shapes when compared with males. Analysis found that females had an approximately 20% choice of the complex image from the pair and male had a lesser choice of approximately 5%, this difference show gender as a significant predictor of preference for fractal complexity (β = 1.585, z = -4.827, p <0.001).

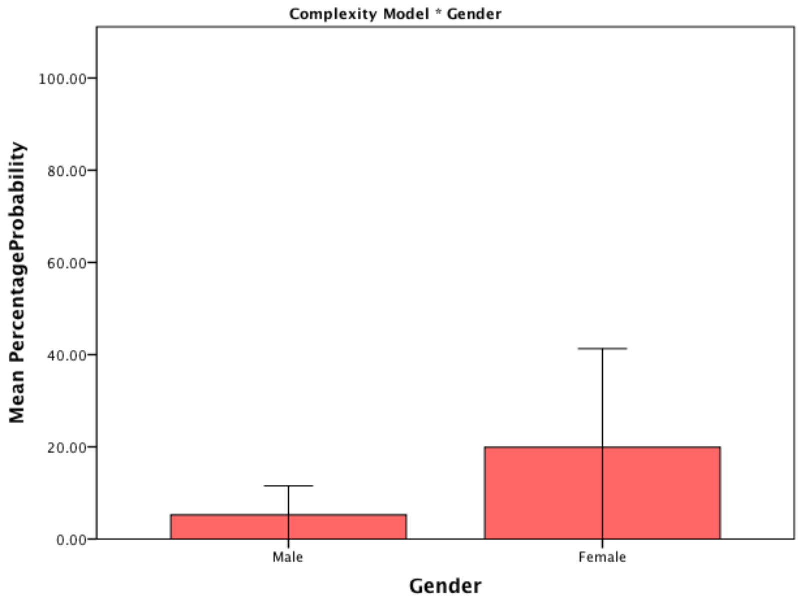


Figure 12.11 Bar Chart of % choice of complex image from a pair across gender

Interaction Effects:

In addition to the main effect of (most) Continents, the analysis found significant interactions in the model.

Although the difference between the continents Africa and Europe was not significant as a main effect, the model shows a significant interaction between Continent (Africa-Europe) and Gender (β=1.446, z = 2.636, p <0.01). With African Males showing an approximately 7% choice of choosing a complex image and African Females showing an approximately 27%, and European Males showing an approximately 10% choice with European Females having approximately a 35% choice of the complex image from the pair.

Interaction effects were also found between Central Asia and Europe and Gender (β=1.446, z = 2.636, p <0.01). As discussed above European Males show an approximately 10% choice with European Females having approximately a 35% choice of the complex image from the pair. Central Asian males had an approximately 1% choice of the complex image and females had a 5% of choosing the complex image from a pair.

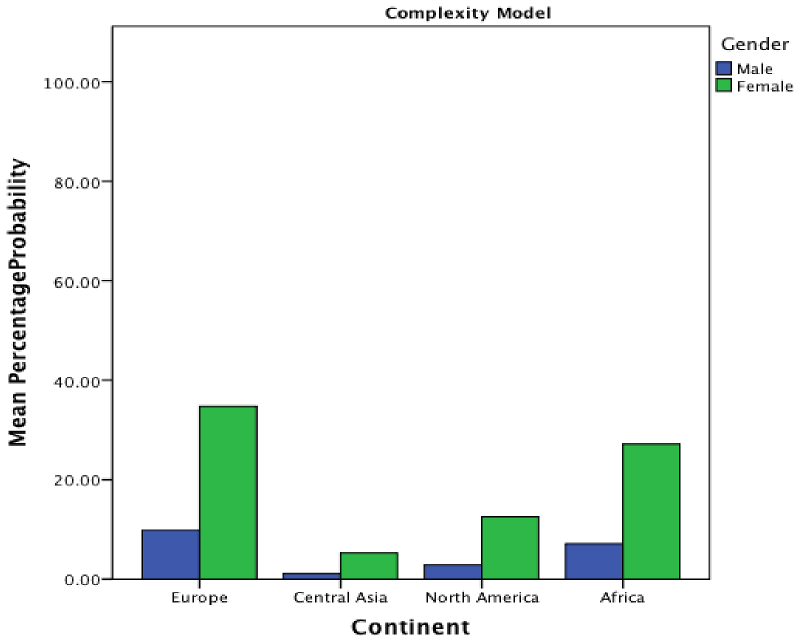


Figure 12.12 Bar Chart of % choice of complex image from a pair across continent and Gender

A significant interaction was also seen between Gender and Age (β=0.028, z = 2.096, p <0.01). As demonstrated in Figure 12.3, Male and Female complexity choices show changes as a function of Age. Female participants preference for complexity decreases with Age, whereas Male participants preference for complexity increases with Age.

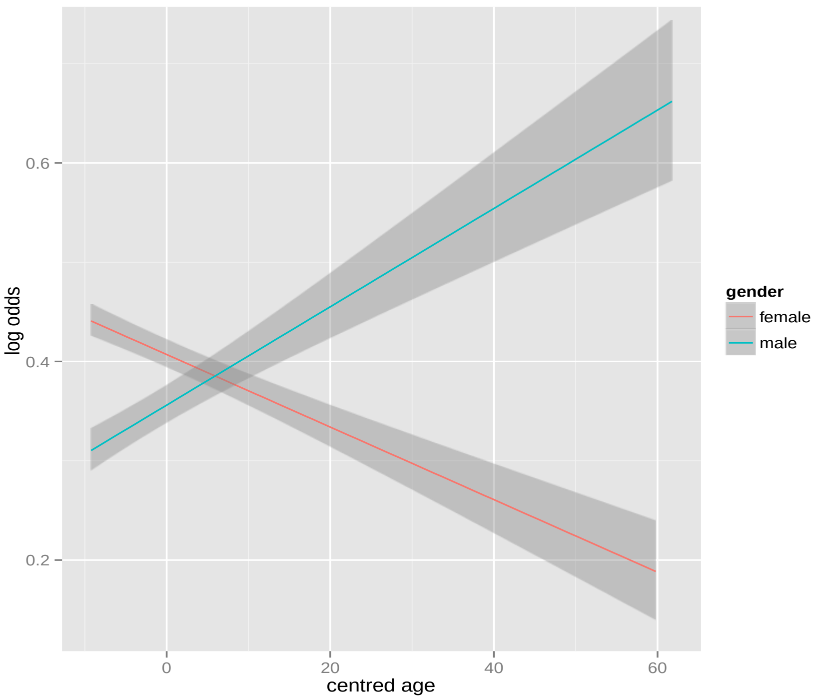


Figure 12.13 Interaction between Gender and Age in Complexity Model

Model B- Mid-Range Model

Mid Range ~ (continent + gender + cAge)^2 + (1 | ID) + (1 | display)

Model B explored the extent to which the variables Continent, Gender and Age could predict the choice of the Mid-Range image from a pair; Table 12.4 shows the main findings.

Table 12.4- results from mid-range model analysis

		β	SE	Z	Pr(>|z|)
Mid-Range hypothesis	Intercept	1.915	0.580	3.304	0.0009 ***
	continent.a-e	0.255	0.231	1.106	0.269
	continent.c-e	-0.198	0.087	-2.262	0.0237 *
	continent.n-e	0.339	0.175	1.937	0.0527 .
	gender.M-F	-0.215	0.106	-2.025	0.0428 *
	cAge	0.001	0.003	0.323	0.747
	continent.a-e:gender.M-F	0.196	0.184	1.063	0.288
	continent.c-e:gender.M-F	0.299	0.133	2.242	0.0249 *
	continent.n-e:gender.M-F	-0.340	0.243	-1.398	0.162
	continent.a-e:cAge	0.034	0.019	1.818	0.0691
	continent.c-e:cAge	0.004	0.006	0.715	0.475
	continent.n-e:cAge	0.008	0.008	1.024	0.306
	gender.M-F:cAge	0.004	0.005	0.814	0.416

*Significance Codes: ***0.001, **0.01, *0.05.*

Overall fit of the model:

Analyses compared the variance explained by the fixed and random effects and explored the extent to which the variables explain the variance in the data. Model B accounts for significantly more variance with fixed and random effects (AIC= 17040, df=21) than the null model with random effects alone (AIC= 17154, df=3), suggesting that the model is improved with the additional variables (χ^2 (18)= 125.14, p<0.001).

Additional goodness of fit analysis found that Continent (χ^2 (15)= 27.887, p<0.05) significantly improves the overall fit of the model; the variable Age marginally improves the model (χ^2 (7)= 12.987, p<0.072) however Gender (χ^2 (7)= 11.811, p=0107) does not significantly add to the overall prediction of the model.

Main Effects:

The model found a main effect of continent on preference for mid-range fractal images (see Figure 12.4). Significant differences in percentage choices were seen between Europe and Central Asia (β=-0.198, z = -2.262, p <0.05). With European samples having an average choice for the mid-range of 85% and Central Asia samples showing an average 83% choice. There are also marginally significant differences in preference choice between European and North American samples (β=-0.339, z = 1.937, p =0.052). European samples demonstrate an 85% choice and North American samples an 89% choice of the mid-range image from a pair.

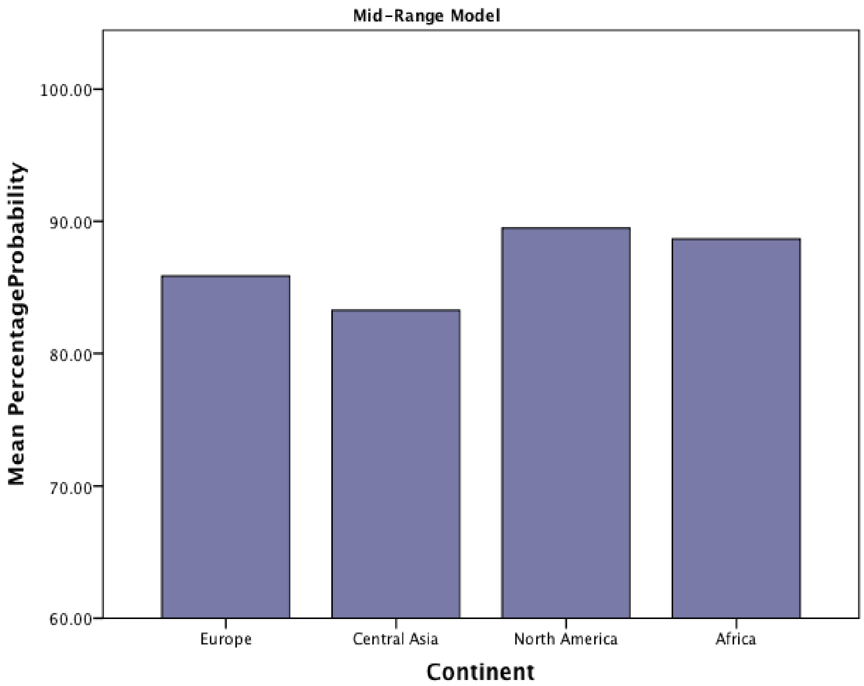


Figure 12.14 Bar Chart of % choice of mid-range image from a pair across continent

In addition the model found a main effect of gender on preference for mid-range fractal images. As demonstrated in Figure 12.15, females show an increase choice in mid-range fractal shapes when compared with males. Analysis found that females had an approximately 88% choice of the complex image from the pair and male had a lesser choice of approximately 86%, this difference show gender as a significant predictor of preference for fractal complexity (β = -0.215, z = -2.025, p <0.05).

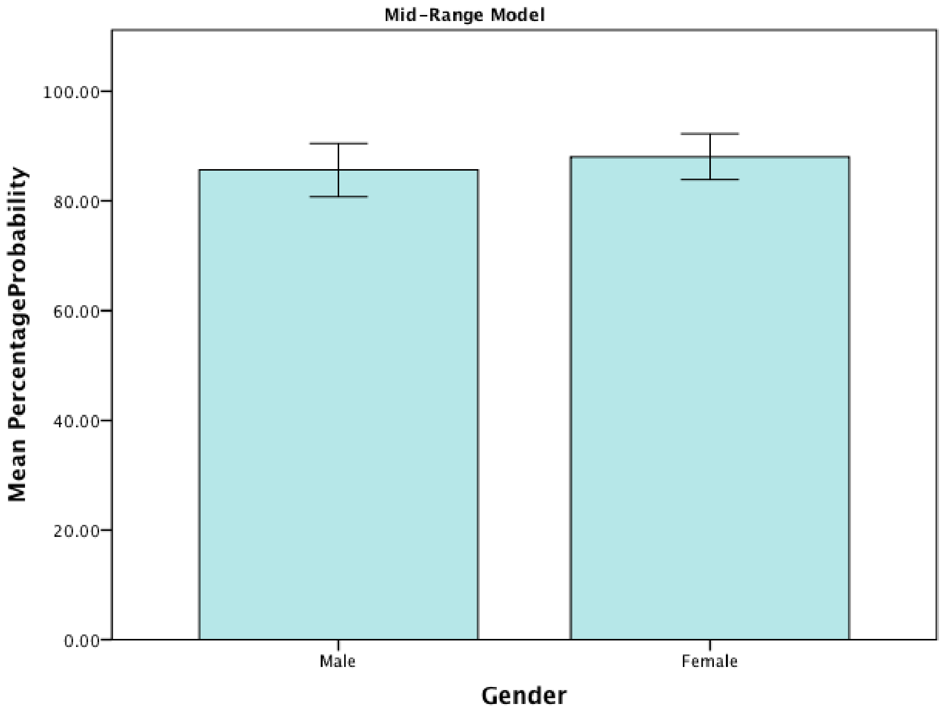


Figure 12.15 Bar Chart of % choice of mid-range image from a pair across gender

Interaction Effects:

Significant interaction was seen between continent (Central Asia-Europe) and Gender (β =0.299, z = 2.242, p <0.05). With European Males showing a preference choice of 85% and European Females an 87% choice of the mid-range from a pair and Central Asian males showing an 82% choice and females an 85% choice. As demonstrated in Figure 12.16, although not significant, females show a consistent preference for mid-range images over males.

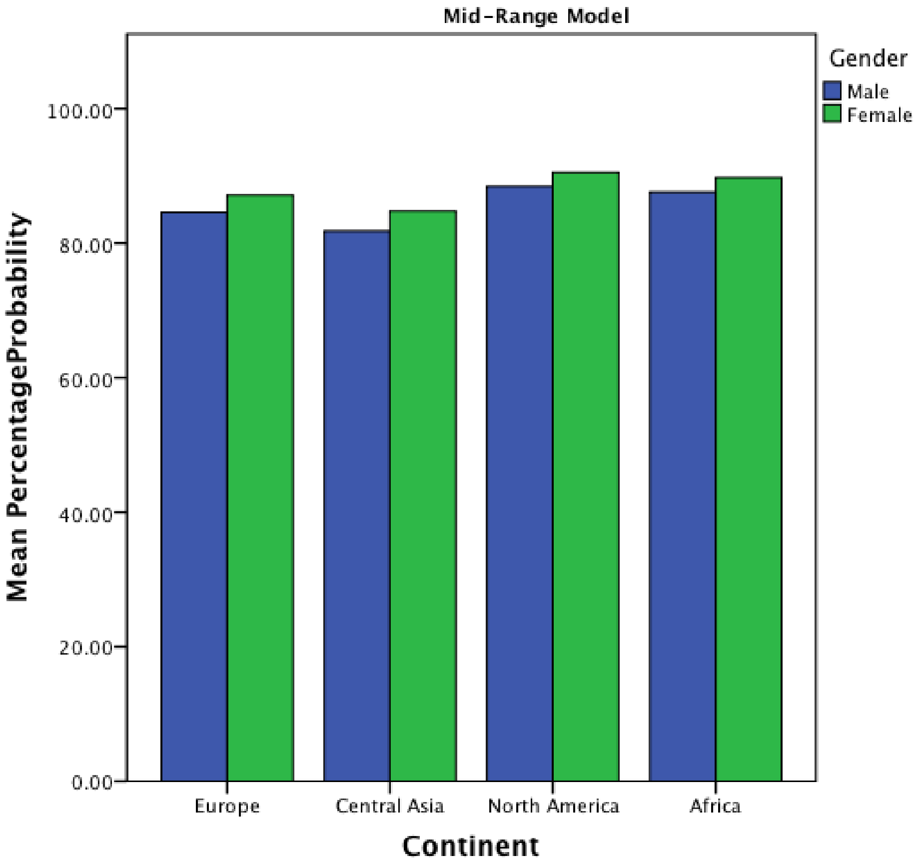


Figure 12.16 Bar Chart of % choice of mid-range image from a pair across Continent and Gender

Results Summary:

Initial frequency choice analysis shows the overall patterns of preference emerging from the sample. The pattern emerging is one of heightened preference for the low to mid range of fractal patterns and falling incrementally with the increases in fractal dimension. When merging the entire 2A-FC data set from this thesis, preferences peak at D1.2, slightly lower than the mid-range reported in literature.

When exploring preference patterns across location, there does appear to be differences in patterns of preference. The European, Central Asian and African sample show similar patterns of preference with peaks at lower-to-mid end of the fractal scale and preference dropping incrementally as fractal dimension (and related complexity) increase. The lowest preference choices in this sample are seen in the high end of the fractal scale. The North American sample demonstrates a different pattern of preference, with highest preferences shown for higher fractal dimension; within this sample (although the smallest populated sample) preference peaks at D1.4 and is lowest across the lower fractal dimensions (D1.1-D1.3).

Patterns of preference were also explored across Gender, and results show that males demonstrate a negative linear relationship between preference choice and fractal dimension with an incremental decrease in preference as fractal dimension increases. Female samples however show a higher peak preference point (D1.6) with less variance across the fractal dimension scales than the Male sample.

Model A found evidence to suggest individual differences including Continent and Gender significant influence preferences for fractal complexity. Results show significant main effects of Gender, with females demonstrating higher preference for complex images than males and a main effect of continent across European and Central Asian, and European and North American samples. European samples show overall a higher preference for fractal complexity. The model also found significant interaction effects between gender and continent (Africa & Europe and Central Asia & Europe) with Gender. In both interactions females show the highest percentage of making a complex choice from a pair. An interaction between gender and age was also discovered within the model and results show an opposite directional effect with male participants preference for complexity increasing with age and female participants preference for complexity decreasing with age.

Model B found evidence to suggest individual differences account for the variance in preference for mid-range fractal images. Main effects of location were shown with significant differences in preference between European and North American samples. North American participants showed a heightened preference for mid-range images. A main effect of Gender also emerged, with females showing a heightened preference choice of the mid-range images. Interaction effects also emerged across gender and location (Central Asia – Europe) with females scoring higher across both sample locations.

Comparing average percentage choices across models, participants show consistently higher choices for mid-range images (around 80-90%) than complex images (ranging from 1-30%) suggesting that preferences are highest for mid-range over complexity.

12.4 Discussion:

The results of this study show the influence of individual differences in fractal preference. The results of the frequency analysis and the LME analysis demonstrate an impact of location and gender on shaping preference pattern for fractal patterns. Overall patterns of preference demonstrate a peak at D1.2, a fractal dimension point below the previously reported peak in the literature, mid-range D1.3-1.5 (Taylor et al., 2011). Looking at the overall preference patterns in the data, a negative linear relationship has emerged, grouping higher preference choices towards the lower end of the fractal scale with preference decreases as fractal dimension/complexity increases. The variability of preference as a function of location and gender does no support the theory of universal preference for mid-range fractal patterns instead results demonstrate the power that individual differences have to shape our visual preference.

Location:

Individual differences have been found to account for some of the variance in preference for fractal patterns, and one such difference appears to be a result of location of residence. The studies recruited a worldwide sample that covered a number of locations/countries, to allow comparisons across locations continent grouping were used. The analysis within this study found significant difference in the patterns of preference as a result of location grouping, suggesting that your residential location shapes your preferences for fractal patterns. The significant differences found in Model's A & B suggest a difference in the preference choice made towards complexity and mid-range fractal patterns. Model A shows on average preferences for a complex image from a pair is relatively low in all groups (between 1-30%) however the prevalence in choice differs as a function of Location and Gender. European samples demonstrate a higher preference for complexity than any other location in the study. Model B also found significant difference in preference for the mid-range images based on location grouping. With North American participants demonstrating the highest percentage choice for the mid-range images. This result suggests that the location in which we spend time influences the preference choices that we make, although the grouping of continent could be criticised as too broad, it demonstrate individual difference

Each analysis included in the study demonstrates significant differences as a result of location, suggesting factors or features of the different locations may contribute to these differences. Previous studies in this thesis have shown environmental classification to be a significant predictor of preference ahead of country grouping and it could be suggested that preference is shaped by the qualities of visual environment in which we spend time. Continent grouping does not allow these specific

Gender:

Models A and B suggest that preference differs as a function of gender; suggesting males and females have different relationships with fractal complexity. Both studies find females more likely to choose a complex or mid-range fractal patterns from a pair however interaction effects within Model A suggest this patterns reverses in the complexity preference with aging. With age, males show higher preference for complexity and females show decreases preference for complexity. This finding suggests a psychological or physiological impact of gender and complex patterns. Some studies have suggested gender is a significant predictor of differences in preference for Art, others believe differences in preference across gender may have deeper evolutionary roots.

Age:

Although increased age samples were recruited to explore the impact of age on preference for fractal patterns analysis did not find any significant main effect of age on preference choice. Model A found an Age x Gender interaction which, as discussed above, raises some interesting questions about the stability of preference across age and other individual differences.

Summary:

These findings offer intriguing insight into the individual differences of preference for fractal patterns, and raise questions about the stability of preference for fractal patterns previously reported in literature (Taylor et al., 2011, Spehar et al, 2003) this result and general findings of this thesis will be explored in the discussion (Chapter 13).

12.5 Alternative multinomial analysis & the limitations:

In addition to the binomial models used to explore the preference for fractal patterns in this thesis, an additional multinomial analysis was also developed to explore the differences between 3 levels of fractal dimension rather than only 2 as seen within the binomial designs. The previous analyses looked at percentage choice based on participants choosing from 2 choices, either the more complex image (complexity model) or the mid-range image (mid-range model). Although this analysis has offered fruitful results throughout this thesis, the authors acknowledge that previous literature which states the presence of 3 categories within the fractal scale (Taylor et al., 2011).

The following analysis explores the data using a multinomial analysis, which allows assumptions to be made about the percentage of choice for the mid-range, but also provide information about the direction of this choice (low or high FD choice). The results and the recognised limitations using this analysis are discussed below.

Table 12.5 Results of Multinomial Analysis

Model	Term	β	SE	Z	Pr(>|z|)
Mid-range hypothesis (Low-Mid-High)	Intercept -high	0.100	1.628	1.648	9.934
	Intercept- low	-0.360	-6.651	-6.663	2.666
	Enviro (high)	-0.302	-3.236	-3.240	0.001***
	Enviro (low)	0.064	0.819	0.824	0.409
	Gender (high)	0.119	1.325	1.310	0.190
	Gender (low)	-0.065	-0.771	-0.761	0.447
	Age (high)	-0.010	-2.902	-2.902	0.003**
	Age (low)	0.005	1.843	1.843	0.065
	Enviro x gender (high)	-0.576	-3.516	-3.516	0.001***
	Enviro x gender (low)	0.082	0.626	0.626	0.531
	Enviro x age (high)	-0.001	-0.126	-0.126	0.899
	Enviro x age (low)	-0.004	-0.929	-0.929	0.352
	Gender (M-F) x Age (high)	0.016	3.214	3.214	0.001***
	Gender (M-F) x Age (low)	-0.01	-2.178	-2.178	0.029*

*Significance Codes: ***0.001, **0.01, *0.05.*

The results show significant interactions across Age and Gender when looking at the mid against high (β =0.016, z = 3.214, p <0.001) and the mid against the low (β =0.01, z = -2.178, p <0.05). The patterns of this interaction can been seen in Figure 12.17. For the Male sample, the probability of choosing fractal patterns in the high category increases with age and the probability of choosing fractal patterns in a low category decreases with age, whereas the probability for choosing the mid-range fractal patterns remains fairly consistent across age. The female sample interestingly shows the opposite direction of probability, with the likelihood of choosing the low fractal patterns increasing with Age and probability of preference for high fractal pattern decreases with age. There appears to be a rise in percentage choice for choosing the mid-range image, although not as steep as the low patterns within the female sample.

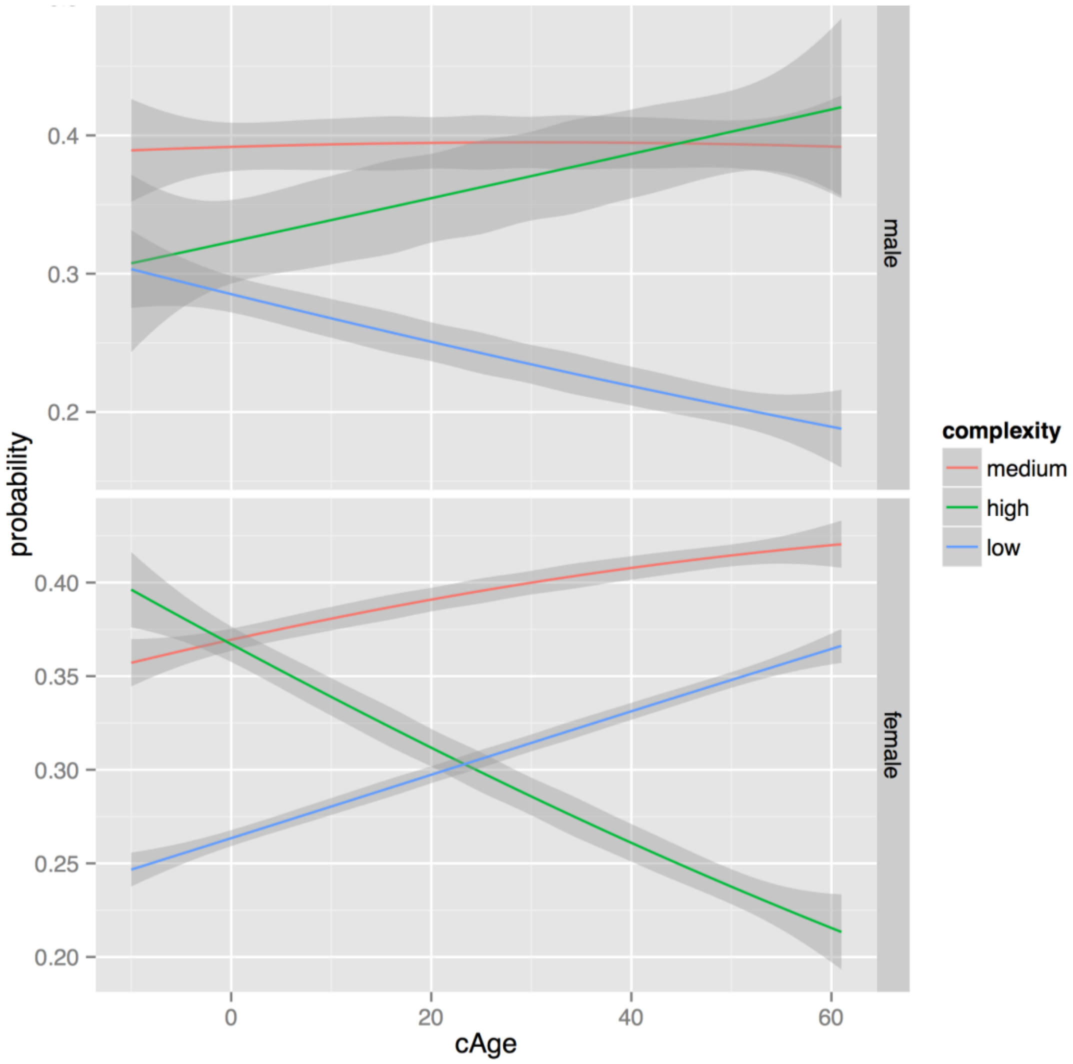


Figure 12.17 – Percentage Choice of 'low', 'mid', 'high' images as a function of age.

Discussion of Multinomial Analysis:

The results of this analysis show significant differences in the preference for fractal patterns across environment, gender and age. The patterns suggest that during ageing, preferences differ significantly between men and women, with women showing higher preference for mid and low complexity within the highest age point and the men showing highest preferences for high and mid images at the highest age point. The findings show individual differences between gender and age and unlike previous binomial analyses we can see patterns of preferences for the full-established fractal aesthetic categories (low - mid - high).

Limitations & Future Directions:

The results of this multinomial mixed-effect model are intriguing, however the method of analysis was not used throughout the entirety of this thesis as it has some fundamental flaws within its design. The model although suitable based on previous literature, suggesting 3 categories of fractal preference, does not match the 2A-FC designed employed throughout this thesis. While this analysis can be conducted, we are in effect, forcing the software to make assumptions of probability for 3 categories when participants were only asked to choose between 2. This was acknowledged during analysis however was included within the thesis to demonstrate the journey of the research and also to suggest fruitful further testing using this analysis. It is suggested that future studies adopt a 3A-FC or ranking design for which this multinomial analysis would be most suited. By using a 3A-FC/ranking design researchers can explore preferences, but also find the direction of these preferences. Current designs allow assumptions to be made about the likelihood of choosing the more complex (Model A) or mid-range (Model B) fractal image however including 3 measures can allow further more stringent investigation of the 3 categorical concept of fractal aesthetics.

13.0 Discussion of Findings:

The aim of this thesis was to re-test some of the established findings towards fractal aesthetics and explore the as-yet, unanswered questions about the extent that individual differences contribute to our aesthetic choices within the fractal scale. This chapter will restate the findings of this thesis in relation to the original hypotheses, followed by an exploration of the implications of the findings and how they fit with current scope of the literature. This thesis has contributed new and novel findings to the field and these are highlighted ahead of making suggestions for future directions based on the findings.

13.1 Hypotheses Table Revisited:

A summary of each study hypothesis within this thesis and their main findings are outlined in Table 13.1, the following discussions will expand on these findings with reference to the existing literature of the field.

Table 13.1- Hypothesis & Summary Results Table

Study One

Fractal Dimension a component of Visual Complexity?

It is hypothesised that the fractal stimulus images will correlate significantly to GIF compression ratio scores; a computational measure of visual complexity. If confirmed this finding would suggest that fractal dimension can be considered as a related component or sub-component of visual complexity.

Summary of Results:

The findings demonstrate support for the hypothesis, that fractal dimension of the stimulus and the GIF compression scores of visual complexity are significant correlated (r=-0.92, $p<0.001$). This finding suggests that fractal dimension and visual complexity are related constructs and as such comparison can be made towards aesthetic responses to both fractal dimension and complexity.

Study Two

Cross-cultural Difference in fractal preference?

Mirroring the samples of Souief & Eysenck's 1971 study exploring the cross-cultural stability of aesthetic preference with UK and Egyptian participants, this study hypothesises that responses to fractal patterns will demonstrate cross-cultural differences for non-art training participants. The study also hypothesises that rating results will support the mid-range hypothesis with highest scores being awarded to images that lie within the D range of 1.3-1.5.

Summary of Results:

The findings demonstrate support for Souief & Eysenck's (1971) findings that non-art trained participant's differed (significantly within the current study) across culture on preferences for fractal complexity. There was no support for the secondary hypothesis; as results found that the mid-point was not the most preferred on the fractal scale. Instead, preference patterns demonstrate a negative linear pattern, rather than a curvilinear pattern found in previous literature.

Study Three

Re-testing the mid range hypothesis:

- It is hypothesised that the overall frequency patterns of preference would display inverted-U shaped function, with heightened preference at the mid-range (D1.3-1.5).

There are three different models of aesthetic patterns explored in this study and as such three different experimental hypotheses:

- It is hypothesised that the variables Country, Age and Gender would significantly predict mid-range model of preference more so than the null model.
- It is hypothesised that the variables Country, Age and Gender would significantly predict linear Complexity model of preference more so than the null model.
- It is hypothesised that the variables Country, Age and Gender would significantly predict Equalized Mid model of preference more so than the null model.

Summary of Results:

- The overall frequency patterns of preference did not display an inverted-U shaped function, with heightened preference at the mid-range (D1.3-1.5), instead overall preference patterns point towards a negative linear relationship between fractal dimension and preference. Preference peaks at the 2nd lowest point of FD (D1.2) and falls incrementally from this point. Preference patterns differed significantly across the different countries in the sample.

There are three different models of aesthetic patterns explored in this study and as such three different experimental hypotheses and the outcomes are discussed below:

- It was hypothesised that the variables Country, Age and Gender would significantly predict mid-range model of preference more so than the null model. Findings show that Continent significantly improved the fit of the model however Gender and Age did not significantly improve the fit of the model. Significant main effect was seen across North American and European samples with significant interactions between Continent (North American – Europe) and Gender.

- It is hypothesised that the variables Country, Age and Gender would significantly predict linear Complexity model of preference more so than the null model. Findings show that Continent significantly improved the fit of the model however Gender and Age did not significantly improve the fit of the model. Significant main effect was seen across North American and European samples.

- It is hypothesised that the variables Country, Age and Gender would significantly predict Equalized Mid model of preference more so than the null model. Findings show that Continent significantly improved the fit of the model however Gender and Age did not significantly improve the fit of the model. No significant main effect were seen in the model however there was a significant interaction between Continent (North American – Europe) and Gender.

The findings demonstrate that individual differences including 'Continent' and 'Gender' can significantly predict difference between preferences for fractal complexity and for the mid-range.

Study Four

Cross & sub-cultural differences in fractal preference:

- It is hypothesised that the overall frequency patterns of preference would display inverted-U shaped function, with heightened preference at the mid-range (D1.3-1.5).

There are three different models of aesthetic patterns explored in this study and as such three different experimental hypotheses are provided below:

- It is hypothesised that the variables Country, Environment, Age and Gender would significantly predict the mid-range model of preference more so than the null model.

- It is hypothesised that the variables Country, Environment, Age and Gender would significantly predict the Complexity model of preference more so than the null model.

- It is hypothesised that the variables Country, Environment, Age and Gender would significantly predict the Equalized Mid model of preference more so than the null model.

Summary of Results:

- The overall frequency patterns of preference display inverted-U shaped function in the UK sample, with heightened preference at the mid-range (D1.4-1.6). The Egyptian Sample however shows less support with results demonstrating a peak at a lower point in the fractal scale.

There are three different models of aesthetic patterns explored in this study and as such three different experimental hypotheses, these and the findings are discussed below:

- It is hypothesised that the variables Country, Environment, Age and Gender would significantly predict the mid-range model of preference more so than the null model. Findings show that Environment and Gender significantly improved the fit of the model, however Country and Age did not. A (marginally) significant main effect was seen across Environmental Classification; in addition a significant interactions was found between Environmental classification and Gender.

- It is hypothesised that the variables Country, Environment, Age and Gender would significantly predict linear Complexity model of preference more so than the null model. Findings show that Environment significantly improved the fit of the model however Country, Gender and Age did not significantly improve the fit of the model. Significant main effect was seen across Environmental Classification; in addition a significant interaction was seen between Environmental classification and Gender.

- It is hypothesised that the variables Country, Environment, Age and Gender would significantly predict Equalized Mid model of preference more so than the null model. Findings show that none of the variables significantly improve the fit of the model more than the null model.

The findings demonstrate that sub-cultural environmental classification (Urban/Rural) is significant predictors of preferences for fractal patterns; this also significantly interacted with Gender in both the mid-range and complexity models. No significant differences were found across country suggesting sub-cultural environment is a better predictor than cross-cultural classifications.

Study Five

Environment, fractal complexity and Connectedness to Nature

Previous studies within the thesis have shown that environmental classification (rural/urban) rather than cross-cultural classification (country) is a significant predictor of preference for complex and mid-range fractal patterns. This study explores potential applications of these differences in preference. As studies have shown that interaction with nature has personal as well as environmental benefits, with those who spend time in nature more likely to take action to protect the environment.

- It is hypothesised that the overall frequency patterns of preference would display inverted-U shaped function, with heightened preference at the mid-range (D1.3-1.5).

There are two different models of aesthetic patterns explored in this study and as such two different experimental hypotheses are outlined below:

- It is hypothesised that the variables Connectedness-to-Nature Score, Environment, Age and Gender would significantly predict mid-range model of preference more so than the null model.

- It is hypothesised that the variables Connectedness-to-Nature Score, Environment, Age and Gender would significantly predict linear Complexity model of preference more so than the null model.

Summary of Results:

- It was hypothesised that the overall frequency patterns of preference would display inverted-U shaped function, with heightened preference at the mid-range (D1.3-1.5). Results show a negative linear relationship between fractal dimension and preference, with preference peaking at the low D1.2 fractal dimension point. Preference drops incrementally from the ‘low’ end of the fractal scale with moderate choices in the ‘mid’ and infrequent choices in the ‘high’ fractal dimension.

There were two different models of aesthetic patterns explored in this study and as such two different experimental hypotheses and the findings are outlined below:

- It is hypothesised that the variables Connectedness-to-Nature Score, Environment, Age and Gender would significantly predict mid-range model of preference more so than the null model. Findings show that Connectedness-to-nature improved the fit of the model however environment, Gender and Age did not significantly improve the fit of the model. There were no significant main or interaction effects.

- It is hypothesised that the variables Connectedness-to-Nature Score, Environment, Age and Gender would significantly predict linear Complexity model of preference more so than the null model. Findings show that Connectedness-to-nature improved the fit of the model and Environmental classification is marginally improves the model however Gender and Age did not significantly improve the fit of the model. There were a significant main effect of environmental classification on preference and a significant interaction between Environmental classification and Age.

The findings show no significant effect of connectedness to nature score on preferences for fractal patterns. The study confirms the environmental classification distinction of preference found in previous studies. In addition, significant main effects for age and preference are evident.

Study Six

Lifespan, Continent & Gender- predictors of fractal preference?

The final study combines all 2A-FC design data from this thesis with the addition of a sample of 'elderly' participants responses.

Age has been found to be a significant (interaction) predictor of preference in study 5 within this thesis, therefore this studies aims to explore this strength of these predictor variables 'Continent', 'Gender' and 'Age' with a wider and more varied sample.

- It is hypothesised that the overall frequency patterns of preference would display inverted-U shaped function, with heightened preference at the mid-range (D1.3-1.5).

There are two different models of aesthetic patterns explored in this study and as such two different experimental hypotheses:

- It is hypothesised that the variables Continent, Age and Gender would significantly predict mid-range model of preference more so than the null model.

- It is hypothesised that the variables Continent, Age and Gender would significantly predict Complexity model of preference more so than the null model.

Summary of Results:

- It is hypothesised that the overall frequency patterns of preference would display inverted-U shaped function, with heightened preference at the mid-range (D1.3-1.5). Findings show that overall the sample shows some evidence to support the hypothesis as the peak of preference at a low-to-mid point of D1.2, with preferences remaining high across D1.3-D1.4 dropping the lowest at the high end of the fractal scale.

There are two different models of aesthetic patterns explored in this study and as such two different experimental hypotheses and findings which are outlined below:

- It is hypothesised that the variables Continent, Age and Gender would significantly predict mid-range model of preference more so than the null model. Findings show that Continent improved the fit of the model, Age marginally improved the model however Gender and did not significantly improve the fit of the model. There was a significant main effect of Continent (Central Asia-Europe & North America-Europe) and Gender. Significant interactions are found between Central Asia-Europe and Gender and Africa-Europe and Age.

- It is hypothesised that the variables Continent, Age and Gender would significantly predict Complexity model of preference more so than the null model. Findings show that Continent and Gender improved the fit of the model however Age did not significantly improve the fit of the model. There was a significant main effect of Continent (Central Asia-Europe & North America-Europe) and Gender. Significant interactions are found between Central Asia-Europe and Gender and North America-Europe and Gender. There was also an additional interaction between Gender and Age.

The findings demonstrate that 'Continent' and 'Gender' are have both main and interaction effects on preferences for complex and mid-range fractal patterns. Results demonstrate that females prefer complexity. Significant cross-cultural differences were also found within the data set. On analysing a wider sample of age variance including an 'elderly' sample, no significant main effect across Age.

13.2 Fractal Dimension as a construct of Visual Complexity:

The first study of this thesis explored if fractal dimension could reliably be classified as an individual construct of visual complexity as a whole. Previous links have found that fractal dimension is perceived as rough and natural. To allow the two models of preferences (mid-range and complexity) to be tested within this thesis, study 1 explored how well fractal dimension (of the stimulus set) and GIF compression ratio scores (an established computational method of quantifying visual complexity), are related. The findings demonstrate strong negative correlations between fractal dimension and visual complexity suggesting that the current findings can be used to make claims about aesthetics responses to a full scale of fractal images, but, also claims about aesthetic responses to visual complexity.

Using GIF compression measures offers a good approximation of human judgments of visual complexity (Forsythe et al., 2008) and is not affected by familiarity effects as human judgments have been found to be (Forsythe et al.,2008). This was an important element as the thesis aims to explore individual differences of aesthetics judgments as a function of both cross and sub-cultural differences as well as differences across gender and age. It was therefore of high importance to ensure that the visual complexity measures adopted were able to quantify strictly. Despite the strong relationship between fractal dimension and visual complexity found in Study 1, the differences between the measures and what can be inferred from them should be discussed.

Fractal dimension measures how rough and self-similar shapes are (see Chapter 3 for full review), this is searching for underlying structures displaying self-similar qualities that cannot be measured using Euclidean geometry. The scores we get from this analysis or during generation are judgments of fractal dimension only rather than any other features of the image. So for example if we had a forest scene (fractal branching in the trees) that also included Euclidean patterns (such as a house or fence) the presence and order in the Euclidean geometry would not affect the overall fractal dimension of the elements in the scene. It is the roughness and self-similarity that is being measured so we cannot add order (using Euclidean shapes) or simplicity into the image and expect it to become less fractal. Fractal dimension of a process or scene is a stable construct. This being said, fractal measurements methods have been used in non-fractal stimulus (see Williams 2013; PhD Thesis) with moderate success but persistent issues remain with these methods, as it is difficult to segregate the fractal and non-fractal content.

Measuring visual complexity using compression techniques in comparison assesses the whole of the image, and attempts to measure each part (whether they be fractal, Euclidean, coloured or monochrome) it does not search for particular patterns but assesses and quantifies the whole image. Some have likened compression measures to methods of visual information processing in the natural world (Donderri, 2006). Donderri suggested information theory as a framework that could explain the success of image compression techniques as a determinant of complexity. Information processing theory see a message or scene as a series of components that are being communicated, these factors include primitive information such as number of elements, colours, contrasts, etc. When the scene contains homogenous elements, there are fewer factors in the string of information to process, but if many items without clear order are included compression techniques report a long information chain, which would take time to process.

Assertions about preferences for levels of complexity can be used within the model, approaches such as the processing fluency theory would state ease of processing is hedonically marked (Reber et al, 2004) in addition environmental studies have found preference for landscapes which maintain interest and facilitate ease in processes but also include elements of mystery suggesting the possibility of further information findings (Kaplan & Kaplan, 1989). Visual complexity allows us to make judgments about a whole visual scene rather than sub-elements of it, as fractal measure does, however it is believed that using both together allows further understanding and ability to quantify experiences in the visual environment.

Overall the findings of the first study in this thesis show that fractal dimension and visual complexity are strongly related, and although we cannot infer direction using correlation, confident conclusions based on how measurements are made as explained above, can be made about the multicomponent nature of visual complexity which have been asserted previously (Nadal, 2007). Visual complexity is an area difficult to define and quantify, and this challenge may be due to an overestimation of the reach of the concept rather than factor with multiple components. This thesis asserts that a multi-component model of visual complexity is accurate and that fractal dimension is one part of this concept; fractal dimension offers us a method to quantify the visual complexity of a specific and psychologically important stimulus; the natural world.

The assertions made above highlight a potential restriction within the thesis, which will be explored in further depth later, however briefly outlined, the use of computer generated fractal stimulus (to allow in depth exploration), despite their established perceptual naturalness (Hagerhall et al., 2004) require testing using real-life visual scenes so comparative studies can be made. One method of doing this is using fractal measurement techniques to measure the fractal dimension of stimulus alongside visual complexity, although studies have previously carried this out with art and photographic stimulus (Forsythe et al., 2010) without significant relationship being reported. New methods such as the Hausdorff's D have emerged that may offer more accurate methods by which to explore the fractal dimension and visual complexity of real-life scenes. This potential future direction will be discussed further later in this chapter (section 13.6).

13.3 Exploring previous models of Fractal Aesthetics:

Studies within this thesis explored the overall patterns of preference by looking at, firstly the ratings of the stimulus in study two, and secondly the frequency of choice between each fractal dimension in studies three to six.

Rating study preference patterns:

The patterns of preference were first examined in the second study within this thesis, which had two main aims. Firstly to explore the mid-range hypothesis for fractal images and secondly to validate a previous study exploring cross-cultural differences in aesthetic responses to complexity with samples from the UK and Egypt (Souief & Eysenck, 1971- furthermore referred to as S&E). The findings demonstrate gender differences within the sample, suggesting that females prefer higher complexity images compared with males. Furthermore age was also found to influence preference ratings for fractal images with participants aged above 20 years preferring simpler images and participants aged 20 years & under rated preferences significantly more for the complex high FD images.

Results also demonstrated cross-cultural differences akin with S & E's (1971) original findings. Non-art-trained 'lay' participants from the Egyptian sample demonstrated high preference for the simple images from the stimulus set (with highest mean ratings given to images of the lowest fractal dimension within the sample, D1.1) and mean rating scores and pattern show a fall with each increase in FD from this point. S & E's sample also find (the non-art-trained) Egyptian participants scored the least complex images the most pleasing. There was less variety across preferences for fractal complexity in the UK sample, opposed to S & E's findings which shows that the highest preferences where shown for complex images

S & E (1971) found differences between cultures, however none were significant across the two sample populations and concluded that their data suggested that there are not large differences between aesthetic preferences in both cultures and instead believe their findings show support for universal theories of preference.

The present studies would not support this conclusion, it seems that while the trend for simple images is still present in the Egyptian (non-art educated) sample, the UK sample did not reflect the same pattern of preference for complexity and differed significantly from the Egyptian sample.

One reason for the differences in finding could be suggested to the stimulus set used within the study, S & E's original study used Birkhoff's (1932) polygons to explore responses to visual complexity whereas the current sample uses pure computer generated fractal patterns. Both stimuli display complexity of a different, but related, kind. Birkhoff's polygons display only Euclidean geometry and this may account for the differences in results. Fractal complexity, although aligned with visual complexity as evidenced in within previous studies within this thesis, is characteristically different from the straight lines and edges seen in many man-made structures (and Birkhoff's polygons) and studies have shown we process fractal images differently to man-made scenes.

In our daily visual experiences we are exposed to both Euclidean and Fractal geometry, in the man made structures and natural processes around us. It could be proposed that the level of interaction and exposure to these shapes influences our preferences for the levels of complexity within them. If we commonly see natural shapes our visual system is experienced at processing them, therefore when assessing their aesthetic value low Fractal patterns may be considered as uninteresting and instead to maintain attention and arousal higher fractal patterns would be preferred. Alternatively, if exposure to fractal complexity over Euclidean geometry/complexity is relatively low then the arousal potential (Berlyne, 1971) that this novelty interest provokes, will peak with any exposure and too much complexity and novelty will be considered busy and be difficult to process fluency, which is hedonically marked (Reber et al, 2004).

If the theories of exposure discussed above are accurate, it could be suggested that the samples between the cultures have been exposed to different visual environments in the UK and Egypt and as such preferences for fractal complexity is markedly different. While these assumptions can be made, further investigation is needed to explore the impact of culture and visual experience of preferences for fractal patterns.

Looking at the sample as a whole, we see generally preferences peak lower than previously found (D1.2) and continues to fall with FD increase. This finding points towards a linear rather than curvilinear relationship between fractal dimension and aesthetic judgment and although potential rationale about visual experience has been offered to account for the differences this requires further testing to be fully understood.

The study used a rating scale for exploring the aesthetic response to fractal patterns, and it is demonstrated from the mean scores that generally participants scores the patterns towards the low end of the scale, which could be a function of rating experience, but alternatively it could be suggested that participants did not find the fractal stimulus used particularly beautiful, therefore found the task difficult to complete accurately. This assertion can be supported by anecdotal evidence from the author that during testing several participants fed back that they did not find any of the stimuli beautiful/appealing suggesting that the rating design may be unsuitable for the stimulus set used. Based on experiences with study 2 in the this thesis, it was decided that a different design would be used to explore preference for the fractal stimulus further that would avoid the pitfalls faced within this study. A forced-choice design was chosen to avoid issues with rating the beauty of the stimulus images and this new method also allowed a different analysis, to be able to predict human preferences for fractal patterns based on a number of individual difference factors, a design and analysis more suited to test the overall aims of this thesis.

Study two within this thesis supported claims that that fractal dimension is an important subcomponent of visual complexity as most of S & E's (1971) findings were replicated suggesting the complexity and fractal dimension are related component. The study also found significant differences between culture, gender and age supporting the further investigation of individual differences as important to understanding aesthetic response to fractal complexity. Finally the study reports only limited support for the mid-range hypothesis and instead supports a more negative linear relationship between fractal complexity and preference. Some potential explanations for the current findings and individual differences have been explored, but it is clear that further studies were needed with the aim to find empirical support and understanding towards these.

Frequency data examining patterns of preference:

Studies three, four and five of this thesis adopted the above changes to the design methodology. In addition to the complexity and mid-range models explored in the following sections, this discussion will explore the overall frequency patterns displayed in 2A-FC methods. The main areas to be examined within this discussion are overall patterns of preference, differences across culture/country, differences cross environment and finally gender differences.

When exploring overall patterns of preference in each study, frequency findings were expected to peak within the ‘mid-range’ of fractal dimension scale. Taylor et al., (2011) exploration of 10 years of perception research on responses to fractal patterns found that patterns falling within the range D1.3-1.5 were most frequency chosen with a 2A-FC design. This theoretical position was tested by exploring patterns of preference against others such as the linear models of preference and complexity found by other researchers (Forsythe et al, 2011).

Study three used a large, cross-cultural sample recruited using Mechanical Turk an online recruitment pool. Overall patterns of preference show that frequency of choices peaked at D1.2, and fell from this point incrementally with increases in fractal dimension. Choice means are relatively similar through the low and mid points of the fractal scale, and fall significantly lower at the high end of the fractal scale. Study four found a peak in preference higher in the overall sample than in study three, with highest frequency choices for stimulus of D1.4 and D1.6 and drops in preference at the lower and higher end of the fractal scale. Patterns of preference in study four support the mid-range hypothesis patterns. Study five found highest preference for lower FD images with a peak in stimulus of D1.2 with grouped drops at the mid and high sections and finally study six found a peak in preference at the lower end of the scale (D1.2) with preferences dropping from this point.

Looking at the data set as a whole, we can see patterns of preference display a peak lower than previously suggested in the literature, most often preference peak at D1.2, only slightly lower than the lowest point in the mid-range hypothesised (D1.3-1.5). The patterns of preference from this point, drops lowest at the highest level of the fractal scale, suggesting consistent patterns of dislike for higher fractal stimulus images. The rationale for this lack of preference in complex images could be explained by theories of visual processing, Reber et al's (2004) processing fluency model suggests that preference peak at the mid-range of complexity because increases in complexity will eventually result in decreases in perceptions of beauty (Reber et al, 2004) the overall patterns of preference offer some support to this theory that high fractal dimension is least preferred.

Differences in visual experience:

Studies three, four & six explored the differences in patterns of preference across continent/country. Preferences were mapped across country (in study four) or continent groupings (in studies three and six) as a result of the number of participants in each country. Preference patterns were unpicked to show the impact of individual differences on fractal preference testing the stability of 'universal' preference previously posited in literature (Spehar et al, 2003; Abraham et al, 2011) and when examined this way, different patterns are evident, suggesting an impact of country/continent in shaping preferences.

In study three the most densely populated continents frequency patterns were compared (Europe, Central Asia & North America) and while Europe and Central Asia show patterns of preference peaking at the low to mid range of the fractal scale, the North American sample demonstrates the opposite pattern with peaks at the highest fractal point (D1.9). One possible reason for the difference in patterns of preference across continent could be the differences in visual experiences across the three locations.

Study six combined the data from all previous 2A-FC design studies, and explored preference across the 3 continent groupings Europe, Central Asia and North America with the addition of Africa in the comparison. European patterns showed relative consistency across the low and mid fractal dimension range with lower preference at the higher end of the fractal scale. The African and Central Asian participants display similar negative linear relationships between fractal dimension and preference choice with preferences peaking at the lower-to-mid range. The North American sample displayed a different pattern of preference, preferences peak at the higher end of the fractal scale and fall lowest at the lowest end of the fractal scale. These results as in study four demonstrate that continent grouping has a significant influence on preferences for fractal patterns. As each distinct continent shows distinct patterns of preference, one could suggest that the differences are a result of visual experiences (or lack of) with the natural and often fractal world.

Study four went some way to explore this and compared the participant's country of residence (UK & Egypt) alongside environmental classification (Urban & Rural) to further explore the impact of visual experience on preference for fractal patterns. The findings show that environmental classification influenced the differences in patterns of preference; with rural participants demonstrating higher preferences for the high end of the fractal continuum and urban participants alternatively had strong preference choices for fractal patterns at the lower end of the fractal scale. One possible explanation for this finding is the ecological variant theory.

The ecological variant theory that exposure to environmental patterns of complexity or those that display fractal properties could potentially be influence and shape aesthetic responses. The mere exposure hypothesis (Zajonc, 1968) states that that exposure to stimulus can result in heightened preferences as we demonstrate higher aesthetic judgment to familiar objects, patterns of scenes. Reber et al., (2004) proposed a processing fluency model, which may account for increased preference with mere exposure as they suggest familiarity results in ease of processes that are hedonically marked. The findings show significant differences in preference pattern for fractal dimension across environment and this could be suggested to be a result of the different visual experience those residing in different environments may have, this conclusion brings into question the impact visual exposure has on our preferences for shapes and structures. Not only on larger macro-scales such as continent and country, but also in terms of smaller micro-scales such as the daily visual experiences from home, work and socializing. The environmental classification in which a person lives, or develops may impact our preference for fractal patterns. As fractal patterns are commonly found in nature, those who develop and live in rural setting are regularly viewing complex fractal patterns (in trees, plants and natural landscapes), people who spend much of their time in urban environments have little exposure to fractal patterns, as man-made structures such as roads, buildings and computer screens do not display fractal complexity. Based on Zajonc (1968) mere exposure hypothesis it could be suggested that higher preference will be shown for the scenes that resemble those you see regularly, therefore urban participant show preference for simple fractal patterns (based on the lack on complexity in their daily visual field) and participant in rural environments will show preference for more complex higher fractal patterns because of the complexity they see in their environment. This assertion needs further testing, the environments in which participants spend most of their time should be investigated to explore if exposure to natural patterns, or lack there of, could be accountable for the differences in linear preference found in this study.

Study five tested the stability of this micro-cultural difference in environmental classification however did not find support when looking at the patterns of preference alone. Both groups (Urban and Rural) display similar patterns of preference that peak at the low end of the fractal scale and drop incrementally with increases in fractal dimension. This result does not support the strong dichotomy found in previous studies in this thesis however one potential explanation of this finding could include the limited sample size. As this study was exploratory only a small size was recruited (N=30) from only one country (Egypt). The extreme negative linear relationship of preference choice and fractal dimension is similar to the patterns of preference found in study three in which Egyptian samples show this type of preference pattern across the fractal scale. Whilst this finding means that the findings of study four should be reviewed cautiously, given the limited sample size and country of origin it could be suggested that this studies findings are not reliable enough to make firm assumptions about the role that environmental classification plays in shaping preferences for fractal patterns.

Alternative suggestions to explain the differences in preference across continent and environment reported above could be individual differences not measured within the study. As discussed in chapter 4, there are many individual factors that have been found to contribute to differences in preferences. These aesthetic responses to the fractal patterns could be related to the education background, experiences with nature/fractals or even attitude of the participants approaching the task. These factors need to be explored in the future in order to allow definitive assertions to be made.

Gender:

All studies explored the role gender plays in shaping patterns of preference for fractal stimuli. Study three found little difference in the patterns of preference across gender, with most choices (in both males and females) made at the lower end of the fractal scale, however the cluster of this is greater for males (whose preference choices peak at D1.2) than females (whose preference peak later at D1.4). Study four found what appeared to be differences in the direction of preference across gender. Females showed an increase choice of higher FD stimulus and males showed and increased choice of the lower FD images. Study five found no differences in patterns of preference across gender, with Male and Females both showing peaks in preference choice at the lower end of the fractal scale, this study. Study six found similar patterns, that males show higher choices for lower fractal dimension, whereas females show more variance and preference peak at a later point in the fractal scale.

Looking at the results as a whole, it can be stated that males on average show higher preference for lower fractal dimension images than females. Male participants show similar negative linear relationships across the studies within this thesis, whereas female participants show heightened preference for fractal patterns of the mid-range and less directional patterns of preference. These finding suggest that gender of participants influences their aesthetic relationship with fractal patterns.

Conclusion about the mid-range hypothesis:

Overall the results of the patterns of preference analysis conducted across each study in this thesis suggest an overall peak of preference lower than previously shown in the literature, which does not support current literature findings suggesting a mid-range peak of preference. Results also show that individual differences including country, environment and gender play a significant role in preference patterns offering evidence to contradict theories that suggest preference for mid-range fractal patterns would be universal (Spehar et al, 2003).

13.4 Complexity Model's Results Explored:

Models of complexity and preference can be traced back to the very early field of empirical aesthetics (Birkhoff, 1933), it has been repeatedly noted that complexity plays a role in aesthetic judgments. There have however been inconsistent findings within the field, which may be based, in the associated difficulty in defining visual complexity as one construct additionally the design and measurement used has varied greatly across disciplines. As noted by Taylor et al (2005) most complexity research has focused on the responses to complexity of scenes made up of Euclidean shapes, this means the applicability of previous findings to nature are limited. The current thesis attempted to add to this field and explore the individual factors that can predictor fractal complexity preference. A series of studies explored models of complexity and preference and the results from the studies and their positioning within the current literature will be explored below.

Studies in the thesis have shown significant cross-cultural differences toward fractal complexity. Study three found significant differences between North America and European participants likelihood to choose the complex fractal images from a pair. Study six revealed significant differences between Central Asia, North America and SE Asia when compared to a European sample.

European samples are three times more likely than the other continents to choose the complex image when presented with a pair of images. In addition to the main effect of continent on fractal complexity preference, continent was also found to interaction significantly with gender. Results found significant interactions between continent (Central Asia and Europe) and gender. Result show that whilst European participants are generally more likely to choose the complex image, there are different directional patterns in probability with males in Central Asia being more likely to pick the complex image and European females being more likely to pick the complex image. There were significant interactions between (Africa-Europe) continent and gender with female participants being most likely to choose the complex image than males in both continent groups.

The cross cultural findings oppose many of the previous studies which find general consistency across cultures for preferences (Eysenck & Iwawaki, 1971; Child & Iwao, 1968; Iwao, Child & Garcia, 1969) it could be suggested that as no such large scale cross-cultural studies have been conducted previously with fractal patterns. Previous studies have found much support for cross-cultural differences with Euclidean geometric complexity. The results of this thesis show that culture, and continent in particular, is a significant predictor of preference for complexity. Additionally visual environment appears to have an influence on preferences for fractal complexity.

One possible explanation for the emerging differences is the visual experiences of people residing in each continent. These assertions are however difficult to support with only continent group because of the highly variant visual experiences within countries and cultures. Even individuals living within the same culture have significantly different experiences within the sub-cultural world. Following this cross-continental finding, sub-cultural environment was explored in additional studies to assess if cross-cultural differences emerge from difference in visual experiences or are a result of other factors yet to be measured within this thesis.

One of the most interesting findings within this thesis is the finding that sub-cultural factors contribute strongly to preferences for fractal complexity. Study four within this thesis found environmental classification to be a strong predictor of preference for complexity. Participants were asked to classify their living environment including ‘Urban’, ‘Suburban’ or ‘Rural’ and findings from study four show significant differences in preference between ‘Urban’ and ‘Rural’ participants. With Rural dwellers were more likely to choose the complex image from a pair.

Differences between preferences of alternative sub-cultural participants have been explored previously, mostly within the field of landscape/environmental planning. As discussed in Chapter 4 within this thesis, studies have shown that preferences for landscape are significantly influences by classifications of the environment. Studies have shown differences between inner city school children and environmental educators (Medina, 1983). Furthermore Dearden (1984) found familiarity with the landscape appeared to be positively correlated with landscape preference and within the study rural dwellers had higher preference for natural landscape over urban and high-density housing environments dwellers. Literature demonstrates that the environment in which participants lived was a powerful predictor of the variance in preference (Dearden, 1984, Zube and Pitt, 1981; Schroeder, 1983; Kaplan & Talbot, 1987) and despite the differences also found between cultures, it has been suggested that cross-cultural differences were weaker predictors of preference than sub-cultural differences in classification (Yu, 1995).

The findings of the current thesis offer strong support for these findings that visual environment can predict preferences for fractal complexity. The overall findings would offer support for the mere exposure hypothesis (Zajonc, 1968) and processing fluency hypothesis (Reber et al, 2004). The environment in which we spend time, and repeated exposure to particular patterns within the natural environment appears to influence our subsequent aesthetic evaluations.

This evidence could be used to make claims regarding the work of Jackson Pollock, previously explored by those interested in fractal aesthetics. A wealth of evidence has explored the work on Jackson Pollock and his 'fractal expressionism' as coined by Richard Taylor. Anecdotal evidence suggests that the art world changed forever when Jackson Pollock moved from downtown Manhattan a busy urban environment to a quiet country town filled with fractal patterns to excite the senses (Taylor et al, 2005). It is suggested that in his new habitat he spent hours sat on his back porch assimilation the natural shapes around him (Potter, 1985). The findings of this thesis would suggest that environment in which we spend time significantly influences our aesthetic relationship with fractal and natural shapes, and as such when Pollock sat taking in the shapes of nature his preferences for complexity began to change. Following the finding that Pollock's iconic painting are not a mess of chaos but carefully dripped representation of the complexity of nature (Taylor, 1999) his paintings were analysed for the level of fractal dimension and three distinct stages were found, early Pollock paintings display low Fractal D, even as low as D1.1 which could be a reflection of his time in Urban Manhattan. Following his move to the rural environment the next two phases of Pollock's artistic style rose dramatically in FD and his 'classical' period can be quantified at approximately FD 1.7 most characteristic patterns. This finding suggest D1.7 appears to be the level of FD strived to by Pollock, with theorists suggesting that if his patterns went over this 'sweet' spot he dialled back until he reached the characteristic complexity within his images.

This sweet spot at D1.7 has been suggested to be a challenge to viewers as it opposes the mid-range hypothesis of universal preference (Spehar et al, 2003;Taylor et al, 2005) however the findings of this thesis would suggest another rationale. Following Pollock's move to a rural environment his worked demonstrated marked increase in fractal complexity, the current findings suggest that rural dwellers have much higher preferences for complexity than those living in an urban environment and as such Pollock's characteristic change in style may be a result of the change in visual environment and subsequent changes in preference for the fractal patterns of nature. While this is only hypothesised, further tests could be conducted to explore the robustness of this idea, including an analysis of rural and urban dwellers aesthetic response toward Pollock's 'early' and 'classic' period pieces to explore if rural dwellers have a greater understanding and aesthetic resonance with the classical period because of the shared preference for complexity above urban dwellers.

This thesis has found strong evidence for differences in preferences as a function of environmental classification. It has been suggested that our immediate visual environments in which we spend time can predict preference for fractal complexity. The effect of visual familiarity has been found to significantly interact with judgments of preference and complexity (Forsythe et al, 2008) and as such we could assert that interaction with Euclidean geometry in urban environments mean fractal patterns of any level will be considered complex and peak levels based on arousal theory will peak lower than those familiar with fractal complexity within the natural world. Visual experiences with to mid-range fractal images have been suggested to be at the core of their powerful aesthetic appeal (Aks & Sprott, 1996) however Aks & Sprott (1996) do not report the environmental background of the participants which as has been shown is a significant preference for fractal complexity.

In addition to cross and sub-cultural individual differences in preference, gender was also found to be a significant main predictor of preference for fractal complexity in each of the studies testing the complexity model. The findings also show significant interactions between continent/environmental classification and gender. A summary of results demonstrates that females are over 3 times more likely to choose the complex image than their male counterparts.

Gender differences in aesthetic judgment has been suggested as a result of our evolutionary ancestry and the results found within this thesis go some way to supporting this hypothesis. It has been proposed brain activity, not simple perceptual processes result in sex differences in aesthetic processing (Cela-Conde et al, 2009). When exploring the neural underpinning to aesthetic experience across sexes Cela-Conde and colleagues (2009) summarized that strong lateralization in men demonstrates reliance on coordinator spatial relations, were as women demonstrate activity in both hemispheres suggesting greater use of categorical spatial relations taking place during aesthetic judgment.

Categorical spatial relations refer to processing of broad categories of location regarding other elements, so judgments are made based on the object in relation to other factors within the scene. Alternatively Coordinator spatial relations refer to precise location in location and accurate distances amongst objects. The different processing styles have been found to correlate with gender and results have shown that in a mental rotation task men use coordinator spatial relations whereas women use categorical spatial relations (Hugdahl et al. 2006).

It is proposed that the findings explored above offer support for the hunter-gather hypothesis that differences in spatial abilities between genders provide a convincing scenario of sex differences based in our evolutionary history, and as a result of the division of labour between sexes (Silverman and Eals, 1992).

The differences in neural activity when viewing scenes are a result of the labour division between hunting (a primarily male activity) requiring coordinator spatial relation processing and mental rotation skills and foraging (a mainly female pursuit) requires categorical spatial relations, including recognition and remembering the content of varied objects and spatial relations between the objects. It could therefore be argued that the differences in neural processes are a result of the different visual strategies. Foraging also required a greater understanding of the complex visual scenes, typically of high fractal complexity if the undergrowth therefore this could account for the heightened preference for high complexity images over simpler fractal patterns as a sign of vegetation.

Females employ categorical spatial relations during aesthetic judgment, this processing relies heavy on long-term memory so associations can be made between previous and current scenes. Suggestions could be made that if long-term memory plays a greater role in women than men, aesthetic judgment particular for scenes woman use memory more that could mean that experiences play a larger role in aesthetic processing than it does in males. One possible interpretation of the findings is that women firstly prefer complex fractal scenes because of the survival potential indicating vegetation and sustenance, in addition as it has been shown that females are more likely to use long-term memory in make aesthetic judgments, the environmental experience for females could be more powerfully related to preferences than males who employ coordinator spatial relations relevant to the specific scene. Hunting and tracking requires orientation in relation to objects (mental rotation skills) and greater understanding of the scene, mid-range fractal landscapes offer the easiest landscape spatial qualities and has been found to be more natural (Hagerhall et al, 2004), therefore it could be proposed that males would display higher preference for mid-range images than females based on this evolutionary need.

If females experiences shape aesthetic preferences more strongly than males we would expect findings to show interactions between gender and environment, the thesis has found significant interaction between both cross-cultural classifications (Africa- Europe) and environmental classifications (Urban-Rural) with gender, which is indeed what findings show.

Literature demonstrates that women tend to be more aware than men of the objects around them even if not related to the task at hand (Silverman & Eals, 1992) suggesting that the impact of environment visual experiences may play a bigger role in shaping preference in women more than men. Women track and navigate using memory rather than spatial problem solving however men outperform women in navigation tasks (Silverman et al, 2000) which could be suggested as a result of coordinator spatial relation processing. Furthermore natural fractal imagery has been suggested to reside in the long-term memory (Geake & Landini, 1997) this in conjunction with gender findings between perceptual processing of aesthetic responses linked to our evolutionary history. Women use memory to locate items in visual scenes, males instead use different immediate spatial strategies.

Of particular interest to this thesis is the finding that neural processes in males and females for mental rotation tasks have been found to have cross-cultural support for this hypothesis (Silverman, Choi & Peters, 2007) adding additional support toward the cross-cultural findings of fractal complexity found within the results of this thesis.

It can be concluded that the results of this thesis offer support for the biological foundation of aesthetic judgment, the hunter-gather hypothesis (Silver & Eals, 1992) offers a strong theoretical account for the gender differences in preference found between genders toward fractal complexity.

Summary of Complexity Model Results:

The results of the complexity models tested suggest that individual differences can predict preference for fractal complexity. Results demonstrate that both macro (continent/culture) and micro (environmental urban/rural) classifications of visual experience alongside biological foundations appear to work separately and together to formulate preferences for fractal complexity. These have innate and experiential foundations. The findings of these models offer support for current literature in approaches to visual complexity as well as dispute some current evidence regarding the universality of preference for fractal patterns. The most strongly supported finding within the field is the preferences for mid-range (rather than complex) fractal patterns, and as such the following section will explore the results of the analysis for the mid-range model and explore the strength of individual differences for preference within this established model for fractal aesthetics.

13.5 Mid-range Models Results Explored:

One of the main aims of this thesis was to explore individual aesthetic responses to mid-range fractal patterns. Based on previous literature in both visual complexity and fractal aesthetics it appears that mid-range fractal images have a powerful aesthetic draw and as such this thesis aimed to explore the stability of the mid-range preference across Culture, Environmental Classification, Gender and Age. The results found both offer, support as well as highlighting potential issues with the current theory of mid-range fractal peak in preference.

Initially in each study, frequency designs were used to explore the overall trends within the patterns of preference. As discussed above, the overall preference patterns show only limited support for the mid-range. Instead studies found that preference appeared to peak lower than the mid-range (D1.2) and lower fractal images were judged as most appealing with preferences falling as fractal dimensions increased from this point. These overall patterns changed when unpicking the impact of environment.

Study 2 shows strong evidence that the Egyptian sample displayed a negative linear preference pattern for the fractal scale; the UK sample however displays much less variety in preference scores. The UK sample patterns showed peak preferences for D1.2-1.3 images (somewhat consistent with the mid-range hypothesis) and significant decreases in preference for fractal images of D1.6-1.7 with scores beginning to rise again after this dip. These studies do not offer empirical support for the mid-range hypothesis across countries. Instead in appears that preferences are a result in individual differences.

To explore this finding further, Study 3 gained a large cross-cultural sample from which to explore the stability of the mid-range hypothesis of preference. Initial analysis revealed that frequency of choice finds D1.2 as the peak preference within the fractal range, and when exploring patterns of preference across continent, preferences differed significantly and instead displays linear patterns of preference dependent on continent. These results offer interesting insight into the overall patterns of preference however further, more sophisticated, analysis models was then explored to discover the power of each variable as a predictor of preference. Results were grouped into continent and the likelihood of choosing the mid-range image was explored as a function of several individual factors.

Analysis show cross-continental main effects between North America and Europe, with North American participants being significantly more likely to choose the mid-range images than the European sample. These findings are consistent with the current literature collected by Prof Taylor and colleagues (Taylor et al, 2011) in a largely north American population. In addition, the significant differences across continent suggest that culture or potentially, differences in visual environment plays a role in preference for mid-range fractals however without further analysis and studies the reason for these differences was not initially clear.

To explore the rationale that visual experiences may shape visual preference in more detail, sub-cultural as well as cross-cultural differences were investigated in subsequent studies. The results of study 4 found marginal sub-cultural significant differences in preference for mid-range fractal patterns. Findings show that rural dwellers are more likely to choose the mid-range fractal images than urban dwellers. One potential rationale for this finding could be that rural dwellers have higher preference for the mid-range fractals because of their perceived naturalness and this is a much more closely matches the environment in which they spend time, previous research has found visual experiences in nature are commonly made up from mainly mid-range fractal patterns (Aks & Sprott, 1996). Studies have also found that fractal patterns falling within the mid-range around D1.3 are perceived as most natural by naïve observers (Hagerhall et al, 2004, Hagerhall, 2005) this preference for mid-range displayed by rural dwellers could be an draw towards natural images with similarities to the environments in which they spend time. Urban dwellers are less likely to chose a mid-range image, this finding alongside the frequency data above could be suggested that urban dwellers have higher preference for lower fractal dimension images. One potential explanation of this finding can be found in the visual complexity perceptual research, Berlyne's (1971) arousal potential theories proposes that visual complexity is perceived positively up to a point until which is keeps attention and allow ease in processing.

The inverted-U hypothesis suggests that preference fall for visual complexity at the point at which processing becomes difficult

These findings could also offer some support for Berlyne's (1971) arousal theory of preference and complexity. Urban dwellers are largely exposed to simple and Euclidean geometry so fractal patterns are liked as they are complex and provoke arousal up until a point (relatively low) at which processing and understanding becomes difficult. The visual environments in which urban dwellers spend time their arousal potential is reached before rural dwellers (whose arousal potential for fractal complex shapes is higher based on familiarity with natural fractal patterns) therefore preferences from rural dwellers are more likely to fall within the mid-range begin to fall from this point. This model could also be used to support the findings of Reber et al's (2004) processing fluency hypothesis, which states that images are hedonically marked with ease of processing. Factors such as familiarity and complexity contribute to overall experiences of perceptual fluency, therefore rural dwellers may find fractal shapes easier to process and as such the point at which perception arousal potential is reached is higher (at the mid-point) than urban dwellers, who preference fell in frequency analysis was found to peak lower, as urban participants generally have little or rare interaction with natural fractal patterns.

The high percentage likelihood of choice found for mid-range images was significantly higher than choice percentages made for the complex image from the pair (discussed in section 13.4). On average percentage choice for mid-range was around the 80% point (compared with 10% or less in complexity models on average) suggesting higher overall preference for mid-range images in all samples. This high percentage choice offers support for the restoration quality of mid-range images, this theory that stronger preference responses will be reported for natural/restorative stimulus in participants experiencing heightened stress or mental fatigue (van den Berg et al, 2003; Staats et al, 2003), some of the environments in which participants spend time (particularly the urban participants) that has higher attentional and processing demands than natural scenes (Kaplan & Kaplan, 1989; Kaplan, 1995; Berman, Jonides & Kaplan, 2008) which may be a result of the fact that human perceptual systems developed in a largely fractal environment (Rogowitz & Voss, 1990) the findings show that there is high percentage choice for mid-range fractal patterns, suggesting that these images have particular aesthetic quality in which participants responded to.

The results from the analysis in chapter 10 found a significant interaction between gender and environment, and results show that males are more likely to select a mid-range image from a pair. Within other chapters there was no significant main or interaction effects of gender but chapter 12 found the opposite result, that females were significantly more likely than males to choose a mid-range image from a pair. The mixed finding of the effect of gender on choices for mid-range fractal patterns could potentially be supported by literature, including the hunter-gather hypothesis (Silverman & Eals, 1992). Previous discussions have outlined this model that males and females differ in the perceptual processing and associated neural underpinning (Cela-conde et al, 2009). This theory suggests that females make use of categorical spatial relations in aesthetic judgments, which have been associated with experiences and memory, rather than assessment based on the environment as it is currently (as seen in coordinator spatial relations in females).

As outlined above, significant gender differences were not consistently found throughout each analysis within this thesis. There was however a high percentage choice for mid-range images across both genders (average 80-90%), one potential rationale for this finding could be the survival benefits associated with landscape displaying approximately mid-range fractal dimension. Orians (1980) savanna hypothesis suggested that spontaneous emotional responses to landscapes that are positive survival or instincts and then preference fall for savanna type landscape (found to display mid-range fractal patterns) because they are most akin with the environment in which we developed and provided shelter and survival benefits. The Savanna hypothesis has been found to be cross-culturally consistent and preferences for savannah-type landscape is seen in individuals, even if they have never had visual interactions with this type of environment (Falk & Balling, 2009). This effect is particularly strong in children (Balling & Falk, 1982).

The refuge theory continues this line of rationale, that preference for visual environment is greatest for those that can offer both shelter and ability to move undetected (Appleton, 1975). Although the refuge theory has been criticised for its limited ability to demonstrate why differences exist across culture, Appleton (1996) addressed these criticisms when he asserted that preferences may well be shaped by culture, experience and historical influence he highlights that the foundations of these trends are not within a vacuum and stem and as such still have links in environmental preferences based upon these evolutionary instincts of aesthetic preference. This rationale could be used to support the current findings within this thesis, while it does seem the biological and evolutionary foundations play a role in shaping our visual preferences for fractal patterns, they are also shaped in part by our current visual and cultural experiences accounting for significant interactions found here.

Other examples of biological and evolutionary based visual preferences can be seen in our aesthetic responses to symmetry. Symmetry preferences can be used to show how preference for abstract geometric forms can be based on evolutionary survival. Symmetry in mate selection as it represents strong genes, or may have been an unintentional by-product of visual shape recognition (Enquist & Arak, 1994). Symmetry is an effect and easily perceived measure of genetic quality (Møller, 1990; Parsons, 1992) and these same conclusions can be drawn about responses to fractal patterns. Fractal D at the mid-range is an effective and easily perceived measure of naturalness and has the most positive psychological and physiological benefit.

Other examples include facial attractiveness, for which distinctions emerge in early infants before learned behaviour could be possible suggesting innate and evolved responses (Langlois et al, 1987). The theory suggests innate responses are shown in infancy and begin to be shaped by our experiences. As our experiences with faces grow we begin to understand society specific visual experiences what 'average' face are and our preferences for faces become more socially and culturally tied. Using this theory as a guide we could propose this type of aesthetic development for fractal patterns also. Innate responses could (and should) be found toward mid-range, but with repeated exposure to other non-mid or non-fractal environments what we consider most aesthetically pleasing will change with experience. Cultural ties reduce and change a typically scene to which we compare new viewing. We eventually learn the norm of the visual environment in which we spend time and these repeated exposure shaped our aesthetic perceptions.

Summary of mid-range findings:

Overall, there was less individual difference reported in the mid-range models compared with the complexity models, and overall preference choice percentages were higher than the complexity model at around 80-90%. The results however also find differences between continent, gender and environment, which opposes established theories, suggesting preference, is universally set at the mid-range (Spehar et al, 2003). The findings are intriguing and point to both biological and experiential factors shaping changes in preference but with some underlying innate or evolutionary preference patterns. This finding notes a current stalemate of the field of psycho-aesthetics, and further analysis is required to unpick the power of experience to influence preferences for fractal patterns.

13.6 Connection to Nature and Applied Empirical Aesthetics:

As one avenue of investigation, this thesis explored if aesthetic responses to fractal patterns were related to how connected individuals feel to nature. The decision to explore this was based on the body of the literature that has suggested the aesthetic draw of fractals is because of their characteristic naturalness (Hagerhall et al, 2004). Although no significant relationship between connection-to-nature scores and fractal preference were found within this thesis one potential explanation of this could be the exploratory nature of the sample made up of only Egyptian participants. It could be suggested that the measure used, the Connectedness to Nature Scale (Mayers & Frantz, 2004- CNS) found no effect because of its lack of cultural validity. Further exploration of the literature following these results found studies which have shown that Egyptian samples behave differently than western samples in environmental awareness, a concept closely linked with connection to nature. Mostafa (2007) found that Egyptian men displayed more environmentally green purchasing than women; a finding opposed to those in the west that show where females demonstrate more environmental awareness. Although based in a different, but related discipline, Lee & Green (1991) claim most major consumer behaviour models have been developed and tested in the west and pay very little attention to cross-cultural settings and it could be suggest that this lack of cross-cultural validity for the measure was the reason that no significant relationship between connection-to-nature and fractal preference was found.

The author believes that the power of natural images and as a related construct fractal dimension, has been demonstrated to be a strong and lasting bond, therefore it would be justified that it would influence how effected we feel for nature. This avenue of research is not closed and further exploration with cross-culturally tested tools is required to understand if the concepts overlap. Following the submission of this thesis data, further data collection on this avenue has been collected (with UK samples) and early analysis is showing promising findings.

13.7 Future Directions:

The current thesis has found significant effects of individual differences on aesthetic responses to fractal patterns. Despite this new finding, further research is needed to continue the growth in the area. Based on the findings of this thesis, the author has highlighted several potentially fruitful areas of investigation for future directions.

Additional Avenues of Analysis:

The first future direction involves a differing analysis and was touched upon within chapter 12. A potentially fruitful area of extension is the proposal of multinomial over binomial analysis as a possible alternative to test the mid-range hypothesis found in previous literature further. Previous literature suggests that fractal preference falls into 3 categories (Low-Mid-High) therefore it could be argued that the current 2A-FC designed employed throughout this thesis (as well as in previous literature) is not a suitable method to unpick these multilevel aesthetic responses. This was acknowledged during analysis however was included within the thesis to demonstrate the journey of the research and also to suggest fruitful further testing using this analysis. It is suggested that future studies adopt a 3A-FC or ranking design for which this multinomial analysis would be most suited. Using a 3A-FC/ranking design researchers can explore preferences but also find the direction of these preferences. Current designs allow assumptions to be made about the likelihood of choosing the more complex (Model A) or mid-range (Model B) fractal image however including 3 measures can allow further more stringent investigation of the 3 categorical concept established in literature of fractal aesthetics.

Measuring the real visual environment:

The evidence within this thesis suggests that environmental features, such as urban and rural environments have significant influence on our preference for fractal shapes. Whilst this gives us an insight into the perceptual relationship with nature as a whole, it is important to note the limitations of the stimulus set used within the thesis. Whilst controlled computer generated fractal images has allowed strong conclusions to be drawn on the findings being a result of fractal dimension rather than other factors, further analysis is required to understand the application to real-life scenery. One such way is photograph real-life scenes and use measures developed to quantify complexity (GIF as discussed previously) and fractal dimension to make links. There are several ways fractal dimension can be measured from an image. One such measure that could be used on photographs and scenes is the Hausdorff D measure of fractal dimension. By allowing stringent measurement of the natural world, and exploring aesthetic responses to these, we can begin to unpick the influence that aesthetic judgment can have on attitude, mood and behaviour. There are a number of potential tool from which the environmental features can be quantified and this points towards a promising, and increasing applied, research direction. Following on from this thinking, the next steps in exploring the consistency of the strong effects found within this thesis is to take the research into a more applied domain and measure for fractal dimension and complexity the role that they play in every day visual experiences and assess the implications of this in a real-life setting. As well as fractal measures of real-life scenes, other measures that can account for Euclidean geometry should be included to investigate how both forms of geometry interact to form aesthetic judgment towards environmental scenes. One such study the author hopes to work on its develop stimulus to explore the ‘peak’ ratio between Fractal and Euclidean geometry, both of these geometries dominant our daily visual experiences and now new measures offer the opportunity to explore the psychological impact of visual experiences in different environmental regions.

Neuroaesthetics/Physiological benefits with fractal patterns explored:

Further possible future directions based on the findings of this thesis include deeper investigations towards aesthetic relationship towards fractal patterns. As discussed previously, the aims of this thesis were to explore the impact of individual differences on fractal preference and also provide groundwork for further neuroaesthetics and physiological response testing towards fractal patterns.

Previous literature provides some evidence to suggest that fractal and natural patterns can have positive psychological and physiological benefits of the viewers (see Chapter 5 for full review) with responses to the mid-range fractal patterns, demonstrating the most powerful restorative qualities. The findings within this thesis suggest there is more variety across peak preference for fractal patterns and they do not, as previously suggested, lay consistently within the mid-range of the fractal scale (D1.3-1.5). As differences in aesthetic judgment have been found, a potential avenue for exploration would be to explore the benefits of fractal patterns on stress reduction as done previously (See Hagerhall et al, 2004) but accounting for individual differences in aesthetic judgments. If aesthetic judgments differ between different environmental groups, could this also suggest that psychological and physiological responses differ too? This is an area that requires exploration and replication of previous studies given the new insight into aesthetic responses based on the findings of this thesis.

Evidence has demonstrated that the visual environment we spend time in can significantly influence our preference for fractal complexity and therefore could this be used to promote health benefits (from both a psychological and physiological stance). If we know what people like based on experiences, and we know positive aesthetic responses are also linked with other feelings of usability, purchase etc. (see Chapter 5) there could potentially be a way of harnessing this effect of the visual environment in improving psychological well being particularly in hospital or institutional settings. Taking into account the current findings one option is to tailor make visual experiences based on predicted preference and explore the neuroaesthetics and physiological responses to fractal patterns to understand not only behavioural responses (preference choices) but also the physiological and neuroanatomical foundations that could contribute to the aesthetic pull of fractal patterns.

These three areas are just a snap shot of the possible fruitful directions the findings of the current thesis can be used. The application of such findings should not be underestimated and may offer way to promote stress reduction, and restorative qualities to increasingly urbanised populations that are loosing connection and contact with nature.

14.0 Conclusions:

The aims of this thesis were to explore visual aesthetic relationships with fractal patterns, and investigate if established aesthetic judgments towards fractal patterns are influenced by individual differences. It was hoped that by using a large and controlled stimulus set of pure fractal patterns, assumptions could reasonably be considered unbiased by additional information within a scene. To summarise the main conclusions, 6 studies were conducted as part of this thesis.

Study 1 assessed the relationship between the fractal stimuli and visual complexity measures (GIF ratio) and found that strong correlations between the 2 concepts, suggesting that the findings based on the current stimuli set can be used to make assertions not only about fractal dimension but also visual complexity.

Study 2 examined the cross-cultural differences in aesthetic judgments of fractal stimuli. Participants from UK and Egypt rated the fractal stimuli set for beauty and findings show marked differences in preference patterns across the fractal scale. In addition study 2 explored the validity of the mid-range hypothesis as the peak point of aesthetic preference within a fractal scale, findings did not support the mid-range hypothesis and instead point to a linear relationship between fractal dimension and aesthetic judgments, with this relationship most notable in the Egyptian sample.

Study 2 suggested cross-cultural differences in preferences, and as such, Study 3 attempted to validate these findings with a larger cross-cultural sample including data from over 30 countries. Analysis found preferences generally peak at lower ends of the fractal continuum (D1.2) and again negative linear patterns of preferences from this point were found for two of the three continents included within the analysis. Additional analysis explore how well individual differences, including continent, gender and age can predict preferences for complex or mid-range fractal patterns, evidence found that continent and gender were both significant predictors in patterns of preferences for fractal patterns. Despite the confirmation of cross-cultural differences, using 'continent' grouping is a largely unsupported method of cross-cultural grouping and as such more controlled samples were sought to explore cross-cultural differences more robustly.

Study 4 used samples from UK and Egypt and also included the additional component of sub-cultural/environmental classification as a potential predictor of fractal preference alongside country, gender and age. Results found no support for cross-cultural predictors as seen previously, however environmental classification was strongly related to preferences for fractal patterns, with rural and urban dweller displaying significant differences in preference for fractal complexity and mid-range fractal patterns.

Study 5 attempted to explore the potential real-life applications of understanding aesthetic judgments of fractal patterns and alongside environmental classification measures (Urban/Rural) this study explored if a psychometric measure of connectedness-to-nature would relate significantly to preferences for complex or mid-range fractal patterns. The results found that environmental classification is a predictor of aesthetic preferences however connectedness-to-nature scales demonstrated no significant relationship with preference choices. Findings from study 5 also show significant interactions between environmental classification and Age, with preferences for complexity falling in rural samples during ageing and increasing in urban samples during ageing.

The final study, attempted to validate continent, gender and age as predictors of preference for fractal stimuli. Study 6 compiles the data from studies 3-5 with an additional sample of 'elderly' participants to provide a larger span of ages from which predictors regarding preferences can be made. Findings demonstrate that continent and gender are significant predictors of preferences for fractal stimuli and as such validate the conclusions made regarding preferences for fractal patterns as a function of culture and gender. Using a larger and more varied sample, findings demonstrate that age is not a stable significant main predictor of preference, as found in study 5.

General Conclusions:

The findings of this thesis show support for both evolutionary foundations as well as the constructivist account of aesthetic preference for fractal patterns. It is proposed that an internationalist approach should be taken when exploring aesthetic responses to fractal patterns. Overall results show that culture, environment and gender are strong and reliable predictors of preference for ‘pure’ fractal patterns, and as such demonstrate that individual differences underlie preferences, rather than falling into a universal ‘peak’ as found in previous literature. The results from this thesis aimed to makes conclusions to an interdisciplinary audience, to avoid similar problems of variance found within the literature during this thesis. It is important that when exploring classifications of our visual experiences, psychologists, landscape architects, designers, artists, geographers and physicists and many other professions work in an interdisciplinary way so results are assessed and shared across the fields. It is hoped that fractal geometry and the findings from the thesis have taken a step towards this goal and shown how the field and previous literature from numerous disciplines can be used to move the field forward as a unified whole which will result in better and more thorough progress than the current trend of sub-disciplinary working. Mandelbrot stated that-

> *“Fractal geometry is not just a chapter of mathematics, but one that helps Everyman to see the same world differently.” (Benoit Mandelbrot, 1982)*

And it is hoped that based on this thesis, interdisciplinary research will progress to help every man, woman and academic to see the same world differently.

Potential Avenues of Research:

There are several potentially fruitful avenues to progress the findings of the current thesis. Here, only pure computer generated fractal patterns were used to explore aesthetic responses in a controlled manner free from other confounding variables. Whilst this results in reliable findings based on fractal dimension (and the related construct, visual complexity) it offers little to the wider field of daily visual experiences that included both fractal and non-fractal content. Now fractal aesthetic responses have been considered alone, further studies should explore the interaction between Fractal and Euclidean geometry in scenes to understand further real-life daily visual experiences. Other potential avenues include neuroaesthetics responses to fractal patterns. Within the current scope of this thesis, investigation regarding the neural underpinning of responses to fractal patterns could not be explored, however now extensive behavioural measures have been explored and aesthetic responses to fractal further understood, we can examine the qualities of fractal responses that go beyond the purely aesthetic. These are only a small selection of the potential avenues of research from the current findings, and this thesis should be considered a stepping-stone to highlight and encourage further exploration into the unexplored.

Concluding statement:

Fractal geometry allows one way from which to explore our visual relationship with the natural environment in further depth. The findings of this thesis demonstrate the role that individual differences both innate and experiential play on forming our aesthetic judgments. It also goes begins to lay the groundwork for future research examining the impact of differences in such aesthetic responses will have on human behaviour in a multitude of settings.

"For many years I had been hearing the comment that fractals make beautiful pictures, but are pretty useless. I was irritated because important applications always take some time to be revealed." (Mandelbrot, 2004)

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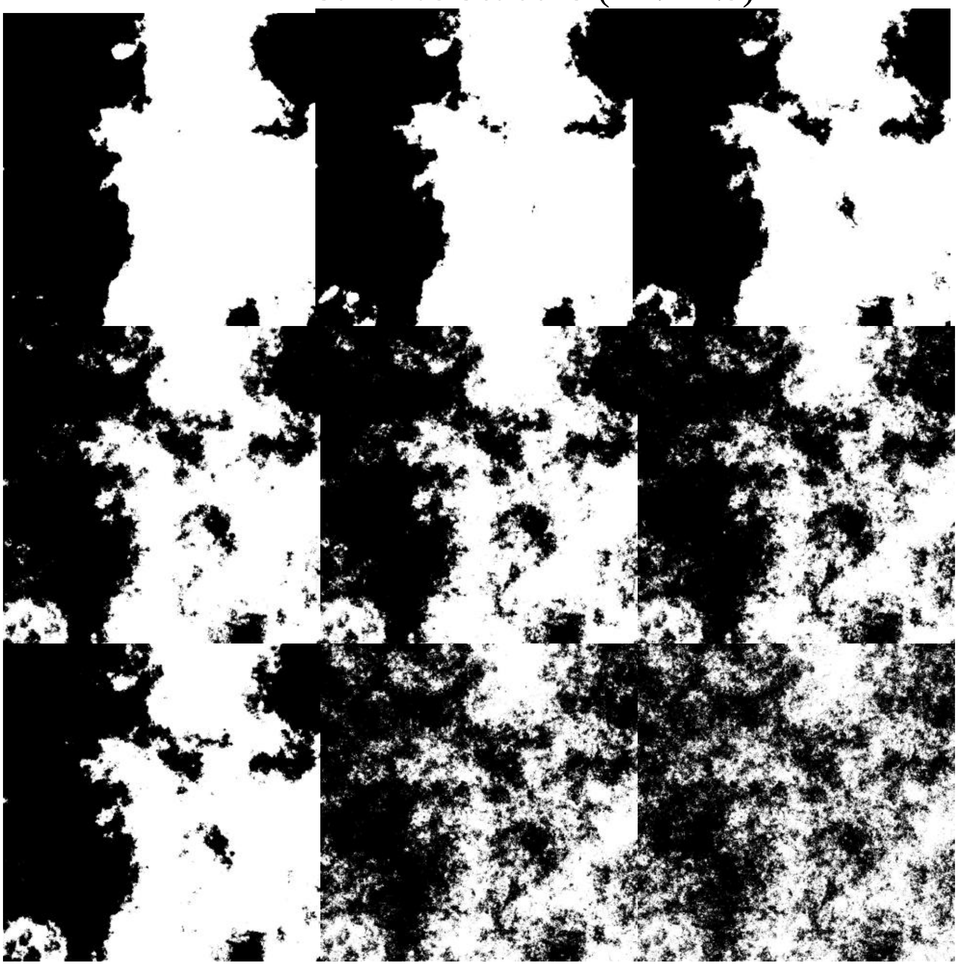
Appendix A: Stimulus Sets

Stimulus Set 0019 (D1.1-1.9)



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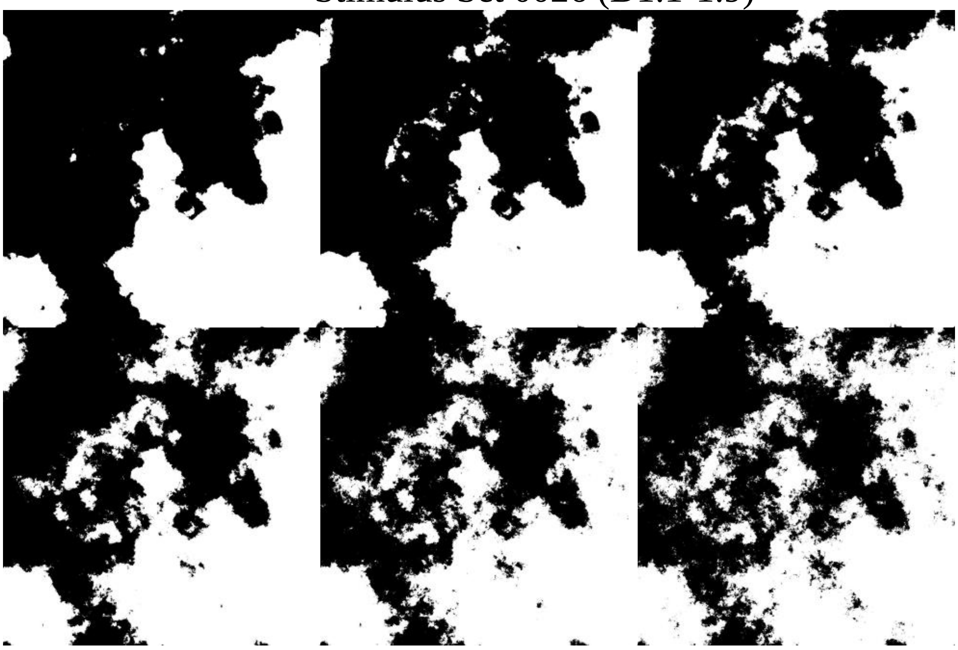

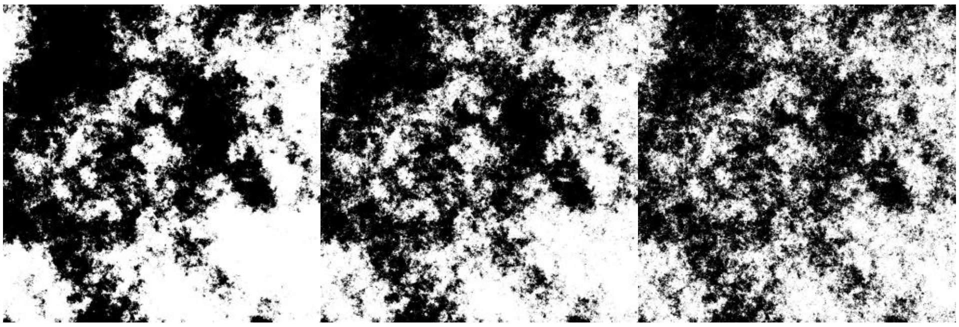

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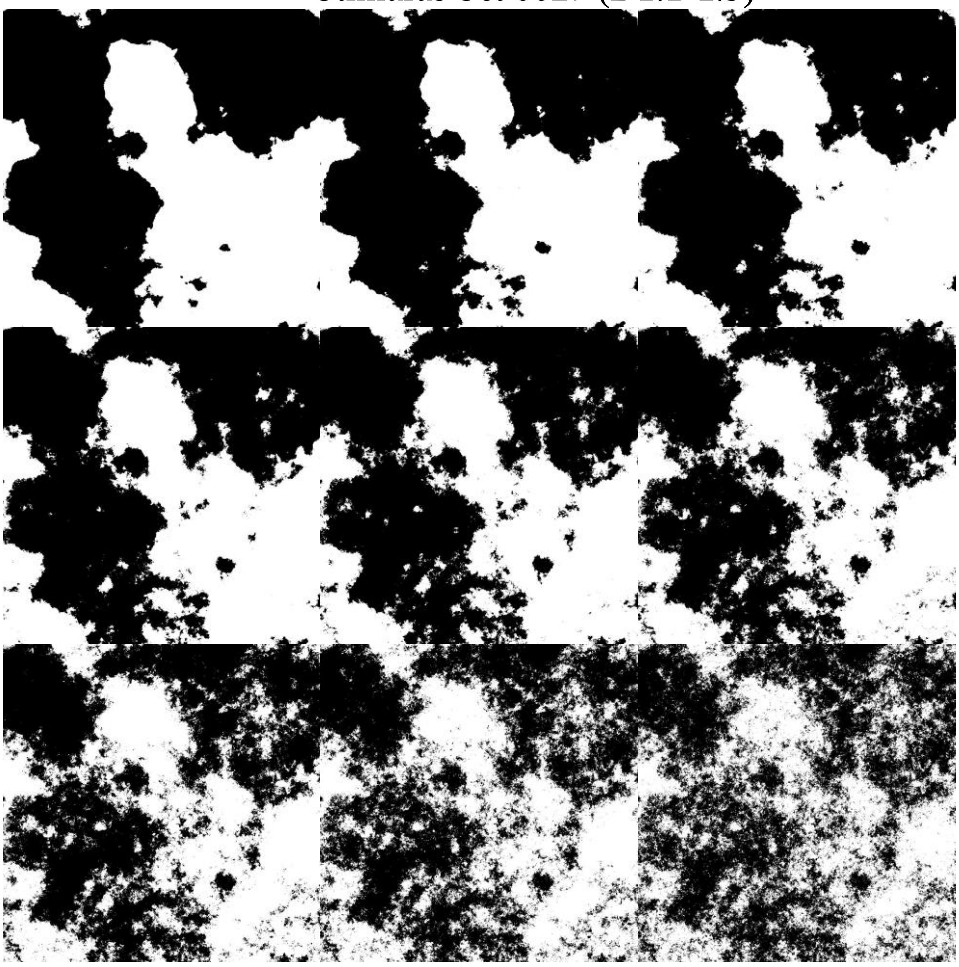

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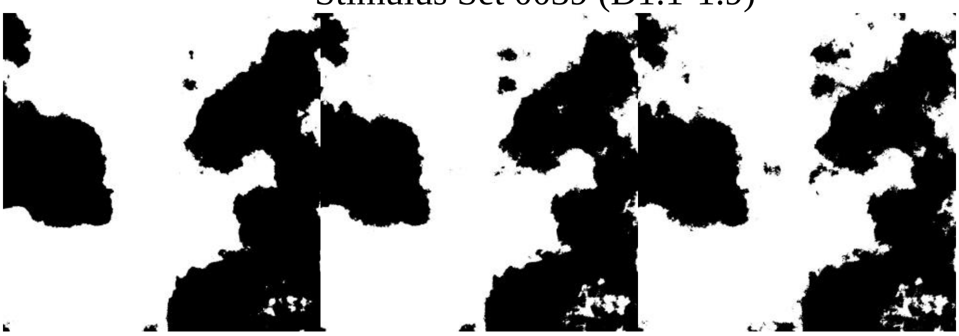

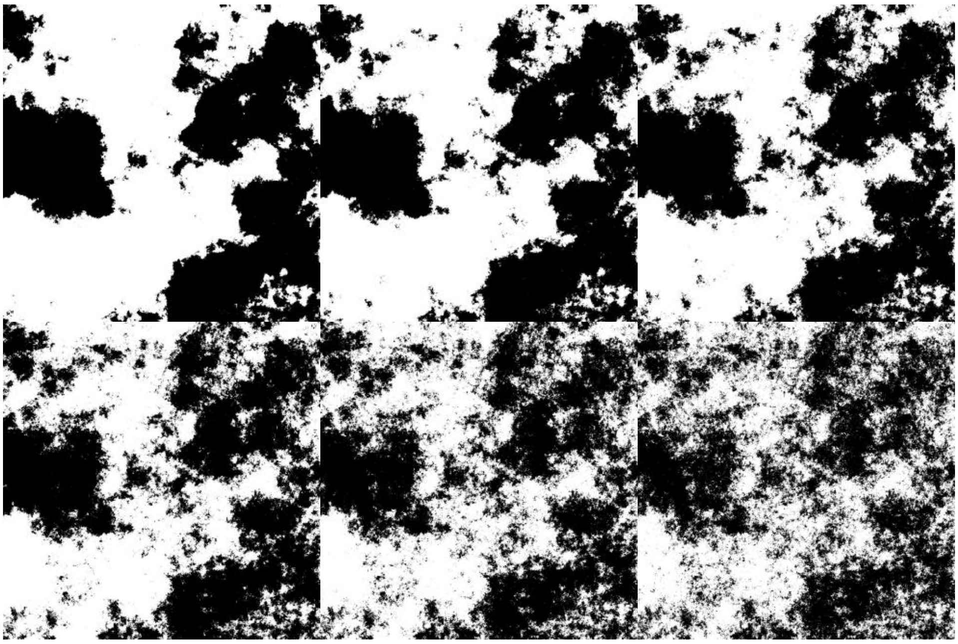

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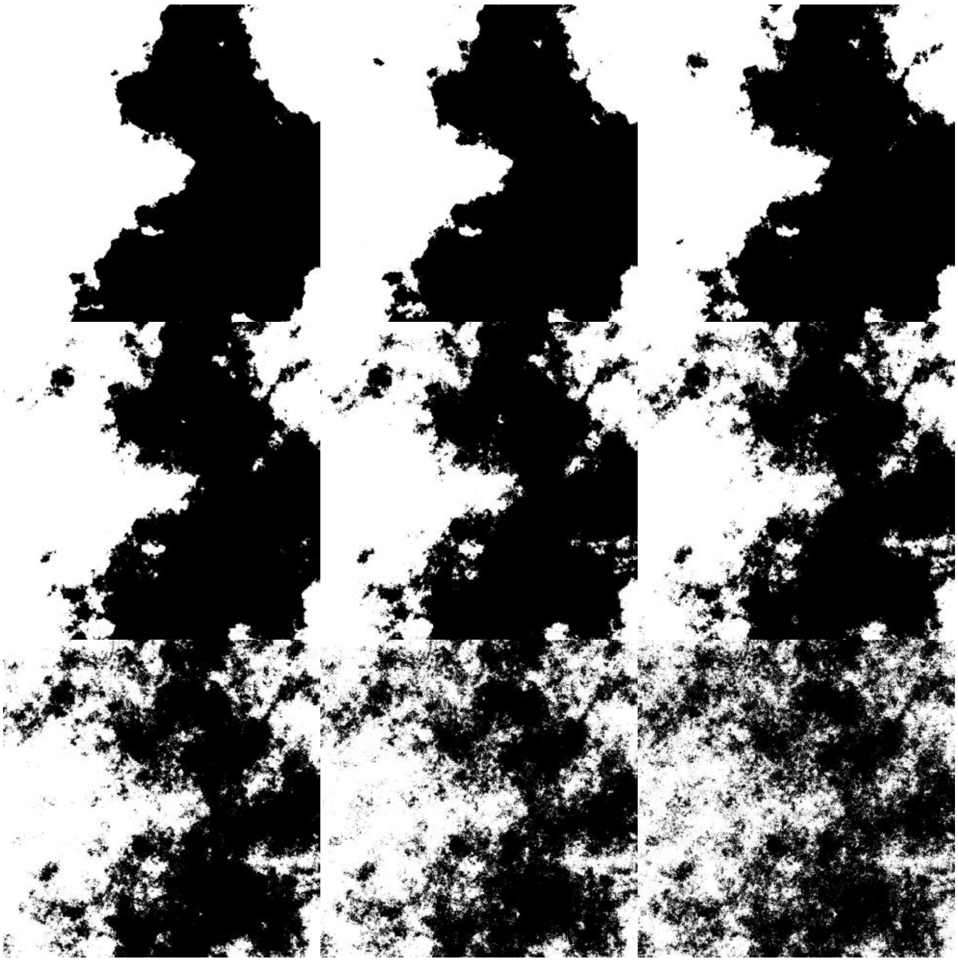
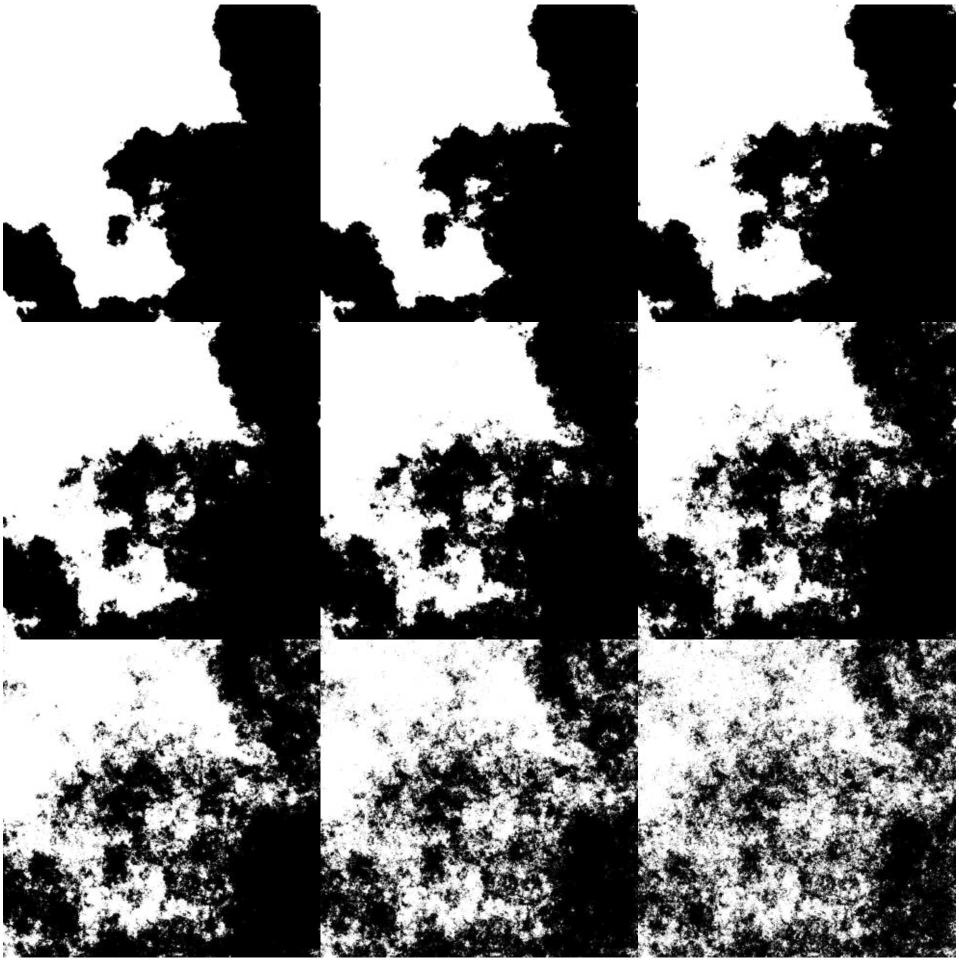
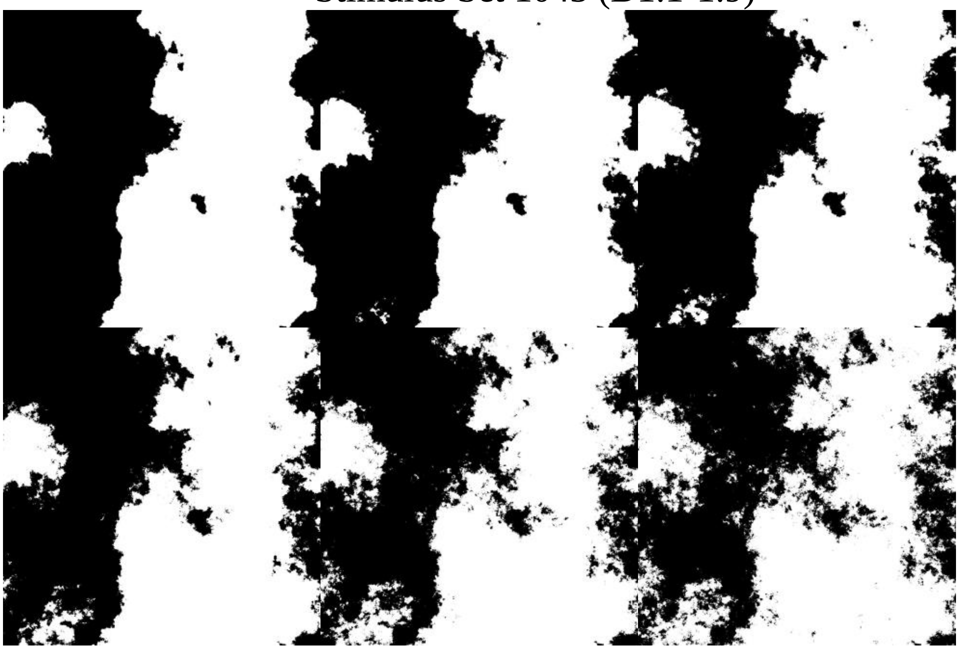
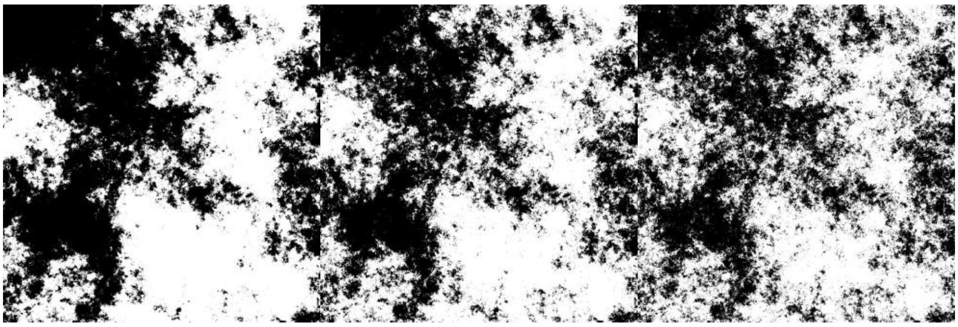


Stimulus Set 0048 (D1.1-1.9)

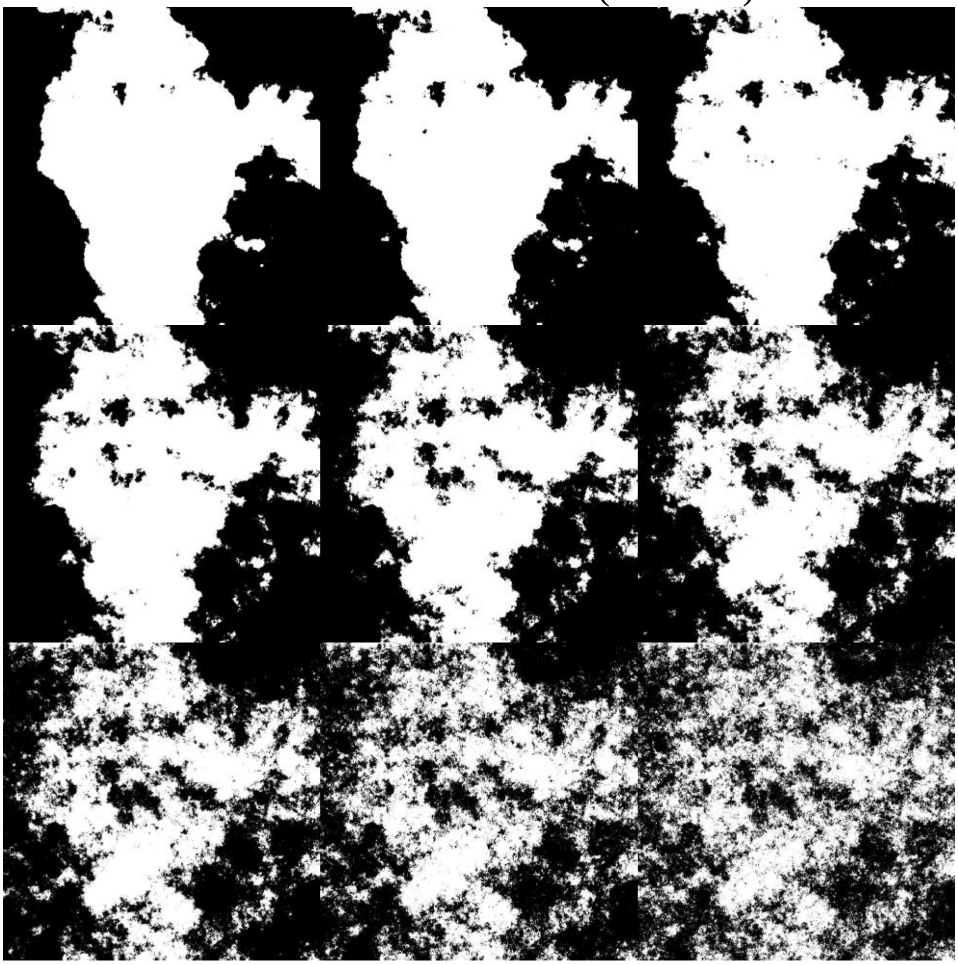


Stimulus Set 1043 (D1.1-1.9)

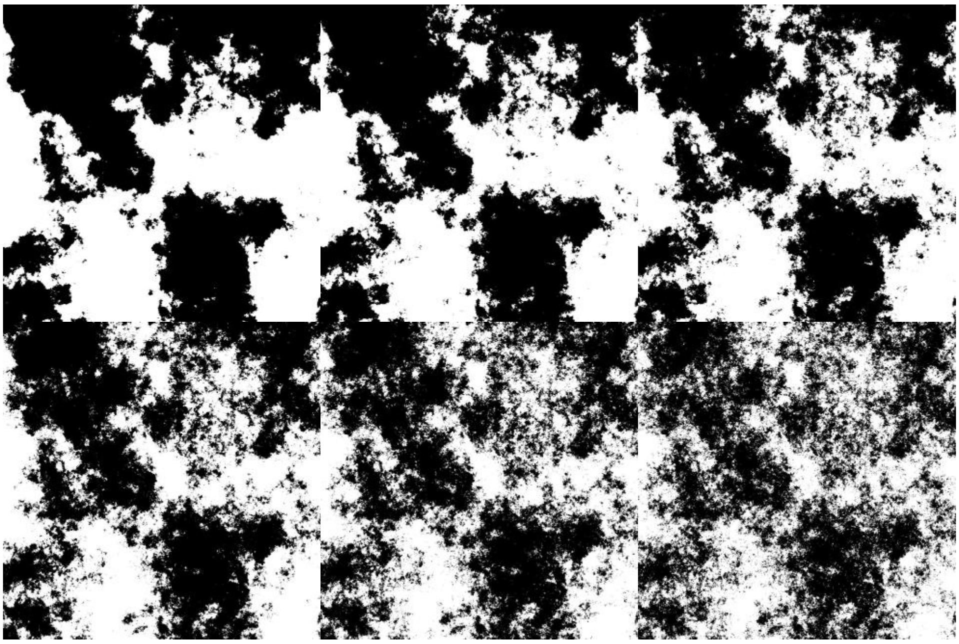




Stimulus Set 1048 (D1.1-1.9)



Stimulus Set 1067 (D1.1-1.9)



Appendix B: Scales

Connectedness to Nature Scale – from Mayer & McPherson-Frantz (2004)

Please answer each of the following questions in terms of the way you feel generally about nature. Please be as honest and candid about what you are presently experiencing.

1. I often feel a sense of oneness with the natural world around me.

- 1- Strongly disagree
- 2- Disagree
- 3- Neutral
- 4- Agree

5- Strongly agree

2. I think of the natural world as a community to which I belong

- 1- Strongly disagree
- 2- Disagree
- 3- Neutral
- 4- Agree

5- Strongly agree

3. I recognize and appreciate the intelligence of other living organisms

- 1- Strongly disagree
- 2- Disagree
- 3- Neutral
- 4- Agree

5- Strongly agree

4. I often feel disconnected from nature *Reverse scored

- 1- Strongly disagree
- 2- Disagree
- 3- Neutral
- 4- Agree
  5- Strongly agree

5. When I think of my life, I imagine myself to be part of a larger cyclical process of living.

1- Strongly disagree

- 2-Disagree
- 3- Neutral
- 4-Agree
5- Strongly agree

6. I often feel a kinship with animals and plants.

- 1- Strongly disagree
- 2- Disagree
- 3- Neutral
- 4- Agree

5- Strongly agree

7. I feel as though I belong to the Earth as equally as it belongs to me.

1- Strongly disagree

- 2- Disagree
- 3- Neutral
- 4- Agree

5- Strongly agree

8. I have a deep understanding of how my actions affect the natural world.

1- Strongly disagree

- 2- Disagree
- 3- Neutral
- 4- Agree

5- Strongly agree

9. I often feel part of the web of life.

- 1- Strongly disagree
- 2- Disagree
- 3- Neutral

- 4- Agree

5- Strongly agree

10. I feel that all inhabitants of Earth, human and nonhuman, share a common 'life force'.

1- Strongly disagree
- 2- Disagree
- 3- Neutral
- 4- Agree

5- Strongly agree

11. Like a tree can be part of a forest, I feel embedded within the broader natural world.

1- Strongly disagree
- 2- Disagree
- 3- Neutral
- 4- Agree
5- Strongly agree

12. When I think of my place on Earth, I consider myself to be a top member of hierarchy that exists in nature. *Reverse scored

1- Strongly disagree
- 2- Disagree
- 3- Neutral
- 4- Agree

5- Strongly agree

13. I often feel like I am only a small part of the natural world around me, and that I am no more important than the grass on the ground or the birds in the trees
- 1- Strongly disagree
- 2- Disagree
- 3- Neutral
- 4- Agree
5- Strongly agree

14. My personal welfare is independent of the welfare of the natural world. *Reverse scored

1- Strongly disagree

-

2- Disagree

-

3- Neutral

-

4- Agree
5- Strongly agree

Appendix C: Analysis Output

Chapter 7 Output:

Correlations

		FD	GIF
FD	Pearson Correlation	1	-.927**
	Sig. (2-tailed)		.000
	N	81	81
GIF	Pearson Correlation	-.927**	1
	Sig. (2-tailed)	.000	
	N	81	81

**. Correlation is significant at the 0.01 level (2-tailed).

Chapter 8 Output:

SPSS Output

Descriptive Statistics

	N	Minimum	Maximum	Sum	Mean	Std. Deviation
1.1	354	.00	10.00	1902.50	5.3743	2.24186
1.2	354	.00	10.00	1772.50	5.0071	1.99698
1.3	354	.00	10.00	1742.00	4.9209	1.82583
1.4	354	.00	10.00	1694.50	4.7867	1.81093
1.5	354	.00	9.50	1589.00	4.4887	1.78795
1.6	354	.00	8.50	1401.50	3.9590	1.78017
1.7	354	.00	9.00	1211.00	3.4209	2.01502
1.8	354	.00	10.00	1144.50	3.2331	2.23956
1.9	354	.00	10.00	1109.00	3.1328	2.49632
Valid N (listwise)	354					

General Linear Model

Descriptive Statistics

	Mean	Std. Deviation	N
1.1	5.3743	2.24186	354
1.2	5.0071	1.99698	354
1.3	4.9209	1.82583	354
1.4	4.7867	1.81093	354
1.5	4.4887	1.78795	354
1.6	3.9590	1.78017	354

1.7	3.4209	2.01502	354
1.8	3.2331	2.23956	354
1.9	3.1328	2.49632	354

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Fractal	Pillai's Trace	.292	17.859[b]	8.000	346.000	.000	.292
	Wilks' Lambda	.708	17.859[b]	8.000	346.000	.000	.292
	Hotelling's Trace	.413	17.859[b]	8.000	346.000	.000	.292
	Roy's Largest Root	.413	17.859[b]	8.000	346.000	.000	.292

a. Design: Intercept
Within Subjects Design: Fractal

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Fractal	.036	1164.311	35	.000	.390	.394	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept
Within Subjects Design: Fractal

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Fractal	Sphericity Assumed	2012.912	8	251.614	72.918	.000	.171
	Greenhouse-Geisser	2012.912	3.124	644.402	72.918	.000	.171
	Huynh-Feldt	2012.912	3.155	638.050	72.918	.000	.171
	Lower-bound	2012.912	1.000	2012.912	72.918	.000	.171

Error(Fractal)	Sphericity Assumed	9744.643	2824	3.451			
	Greenhouse-Geisser	9744.643	1102.662	8.837			
	Huynh-Feldt	9744.643	1113.640	8.750			
	Lower-bound	9744.643	353.000	27.605			

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	Fractal	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Fractal	Linear	1936.279	1	1936.279	132.740	.000	.273
	Quadratic	11.064	1	11.064	3.885	.050	.011
	Cubic	22.804	1	22.804	11.528	.001	.032
	Order 4	33.699	1	33.699	18.979	.000	.051
	Order 5	6.366	1	6.366	3.758	.053	.011
	Order 6	2.269	1	2.269	1.679	.196	.005
	Order 7	.421	1	.421	.291	.590	.001
	Order 8	.010	1	.010	.005	.943	.000
Error(Fractal)	Linear	5149.204	353	14.587			
	Quadratic	1005.434	353	2.848			
	Cubic	698.314	353	1.978			
	Order 4	626.791	353	1.776			
	Order 5	598.065	353	1.694			
	Order 6	477.003	353	1.351			
	Order 7	509.672	353	1.444			
	Order 8	680.161	353	1.927			

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	57768.337	1	57768.337	5958.531	.000	.944
Error	3422.357	353	9.695			

Estimated Marginal Means
Fractal

Estimates

Measure: MEASURE_1

Fractal	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	5.374	.119	5.140	5.609
2	5.007	.106	4.798	5.216
3	4.921	.097	4.730	5.112
4	4.787	.096	4.597	4.976
5	4.489	.095	4.302	4.676
6	3.959	.095	3.773	4.145
7	3.421	.107	3.210	3.632
8	3.233	.119	2.999	3.467
9	3.133	.133	2.872	3.394

Pairwise Comparisons

Measure: MEASURE_1

(I) Fractal	(J) Fractal	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	95% Confidence Interval for Difference[b] Upper Bound
1	2	.367*	.111	.038	.009	.725
	3	.453*	.115	.004	.082	.824
	4	.588*	.119	.000	.205	.970
	5	.886*	.136	.000	.448	1.324
	6	1.415*	.158	.000	.905	1.926
	7	1.953*	.180	.000	1.372	2.535
	8	2.141*	.198	.000	1.503	2.780
	9	2.242*	.212	.000	1.558	2.925
2	1	-.367*	.111	.038	-.725	-.009
	3	.086	.098	1.000	-.230	.402
	4	.220	.107	1.000	-.124	.565
	5	.518*	.130	.003	.100	.936
	6	1.048*	.140	.000	.598	1.498
	7	1.586*	.164	.000	1.056	2.116
	8	1.774*	.180	.000	1.195	2.353
	9	1.874*	.194	.000	1.250	2.498
3	1	-.453*	.115	.004	-.824	-.082
	2	-.086	.098	1.000	-.402	.230
	4	.134	.097	1.000	-.178	.446
	5	.432*	.108	.003	.083	.782
	6	.962*	.122	.000	.568	1.355

	7	1.500*	.146	.000	1.028	1.972
	8	1.688*	.162	.000	1.166	2.210
	9	1.788*	.177	.000	1.217	2.360
4	1	-.588*	.119	.000	-.970	-.205
	2	-.220	.107	1.000	-.565	.124
	3	-.134	.097	1.000	-.446	.178
	5	.298	.102	.136	-.031	.627
	6	.828*	.112	.000	.467	1.189
	7	1.366*	.137	.000	.924	1.808
	8	1.554*	.146	.000	1.082	2.026
	9	1.654*	.170	.000	1.107	2.200
5	1	-.886*	.136	.000	-1.324	-.448
	2	-.518*	.130	.003	-.936	-.100
	3	-.432*	.108	.003	-.782	-.083
	4	-.298	.102	.136	-.627	.031
	6	.530*	.109	.000	.178	.881
	7	1.068*	.118	.000	.687	1.448
	8	1.256*	.140	.000	.804	1.708
	9	1.356*	.157	.000	.849	1.862
6	1	-1.415*	.158	.000	-1.926	-.905
	2	-1.048*	.140	.000	-1.498	-.598
	3	-.962*	.122	.000	-1.355	-.568
	4	-.828*	.112	.000	-1.189	-.467
	5	-.530*	.109	.000	-.881	-.178
	7	.538*	.102	.000	.210	.866
	8	.726*	.114	.000	.358	1.094
	9	.826*	.134	.000	.396	1.257
7	1	-1.953*	.180	.000	-2.535	-1.372
	2	-1.586*	.164	.000	-2.116	-1.056
	3	-1.500*	.146	.000	-1.972	-1.028
	4	-1.366*	.137	.000	-1.808	-.924
	5	-1.068*	.118	.000	-1.448	-.687
	6	-.538*	.102	.000	-.866	-.210
	8	.188	.096	1.000	-.121	.496
	9	.288	.112	.372	-.072	.648
8	1	-2.141*	.198	.000	-2.780	-1.503
	2	-1.774*	.180	.000	-2.353	-1.195
	3	-1.688*	.162	.000	-2.210	-1.166
	4	-1.554*	.146	.000	-2.026	-1.082
	5	-1.256*	.140	.000	-1.708	-.804
	6	-.726*	.114	.000	-1.094	-.358

	7	-.188	.096	1.000	-.496	.121
	9	.100	.085	1.000	-.175	.375
9	1	-2.242*	.212	.000	-2.925	-1.558
	2	-1.874*	.194	.000	-2.498	-1.250
	3	-1.788*	.177	.000	-2.360	-1.217
	4	-1.654*	.170	.000	-2.200	-1.107
	5	-1.356*	.157	.000	-1.862	-.849
	6	-.826*	.134	.000	-1.257	-.396
	7	-.288	.112	.372	-.648	.072
	8	-.100	.085	1.000	-.375	.175

Based on estimated marginal means

*. The mean difference is significant at the

b. Adjustment for multiple comparisons: Bonferroni.

Multivariate Tests

	Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Pillai's trace	.292	17.859[a]	8.000	346.000	.000	.292
Wilks' lambda	.708	17.859[a]	8.000	346.000	.000	.292
Hotelling's trace	.413	17.859[a]	8.000	346.000	.000	.292
Roy's largest root	.413	17.859[a]	8.000	346.000	.000	.292

Each F tests the multivariate effect of Fractal. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

General Linear Model

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
FractalLevel	Pillai's Trace	.284	69.704[b]	2.000	352.000	.000
	Wilks' Lambda	.716	69.704[b]	2.000	352.000	.000
	Hotelling's Trace	.396	69.704[b]	2.000	352.000	.000
	Roy's Largest Root	.396	69.704[b]	2.000	352.000	.000

a. Design: Intercept

Within Subjects Design: FractalLevel

b. Exact statistic

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b] Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FractalLevel	.526	225.985	2	.000	.679	.680	.500

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept

Within Subjects Design: FractalLevel

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
FractalLevel	Sphericity Assumed	3436.069	2	1718.035	114.123	.000
	Greenhouse-Geisser	3436.069	1.357	2531.974	114.123	.000
	Huynh-Feldt	3436.069	1.360	2525.630	114.123	.000
	Lower-bound	3436.069	1.000	3436.069	114.123	.000
Error(FractalLevel)	Sphericity Assumed	10628.264	706	15.054		
	Greenhouse-Geisser	10628.264	479.046	22.186		
	Huynh-Feldt	10628.264	480.249	22.131		
	Lower-bound	10628.264	353.000	30.108		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	FractalLevel	Type III Sum of Squares	df	Mean Square	F	Sig.
FractalLevel	Linear	3308.517	1	3308.517	131.371	.000
	Quadratic	127.552	1	127.552	25.905	.000

Error(FractalLevel)	Linear	8890.163	353	25.185		
	Quadratic	1738.101	353	4.924		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	108441.706	1	108441.706	6064.371	.000
Error	6312.266	353	17.882		

Estimated Marginal Means

FractalLevel

Estimates

Measure: MEASURE_1

FractalLevel	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	12.022	.216	11.596	12.447
2	10.595	.176	10.249	10.942
3	7.698	.240	7.226	8.171

Pairwise Comparisons

Measure: MEASURE_1

(I) FractalLevel	(J) FractalLevel	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	95% Confidence Interval for Difference[b] Upper Bound
1	2	1.427*	.214	.000	.912	1.941
	3	4.323*	.377	.000	3.416	5.231
2	1	-1.427*	.214	.000	-1.941	-.912
	3	2.897*	.259	.000	2.274	3.520
3	1	-4.323*	.377	.000	-5.231	-3.416
	2	-2.897*	.259	.000	-3.520	-2.274

Based on estimated marginal means

*. The mean difference is significant at the

b. Adjustment for multiple comparisons: Bonferroni.

Multivariate Tests

	Value	F	Hypothesis df	Error df	Sig.
Pillai's trace	.284	69.704[a]	2.000	352.000	.000

Wilks' lambda	.716	69.704[a]	2.000	352.000	.000
Hotelling's trace	.396	69.704[a]	2.000	352.000	.000
Roy's largest root	.396	69.704[a]	2.000	352.000	.000

Each F tests the multivariate effect of FractalLevel. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.
a. Exact statistic

Descriptive Statistics[a]

	N	Minimum	Maximum	Mean	Std. Deviation
1.1	200	1.50	10.00	5.9925	1.88119
1.2	200	.00	10.00	5.3600	1.84047
1.3	200	.00	10.00	5.1425	1.74389
1.4	200	1.00	10.00	4.9100	1.75708
1.5	200	.00	9.50	4.4025	1.70404
1.6	200	.00	8.50	3.7050	1.63519
1.7	200	.50	9.00	2.7725	1.47832
1.8	200	.00	9.00	2.4000	1.43450
1.9	200	.00	10.00	2.1725	1.53976
Valid N (listwise)	200				

a. EGYPT OR UK SAMPLE = EGYPT

EGYPT OR UK SAMPLE = EGYPT

Descriptive Statistics[a]

	Mean	Std. Deviation	N
1.1	5.9925	1.88119	200
1.2	5.3600	1.84047	200
1.3	5.1425	1.74389	200
1.4	4.9100	1.75708	200
1.5	4.4025	1.70404	200
1.6	3.7050	1.63519	200
1.7	2.7725	1.47832	200
1.8	2.4000	1.43450	200
1.9	2.1725	1.53976	200

a. EGYPT OR UK SAMPLE = EGYPT

Multivariate Tests[a,b]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Fractal	Pillai's Trace	.789	89.576[c]	8.000	192.000	.000	.789
	Wilks' Lambda	.211	89.576[c]	8.000	192.000	.000	.789
	Hotelling's Trace	3.732	89.576[c]	8.000	192.000	.000	.789

	Roy's Largest Root	3.732	89.576[c]	8.000	192.000	.000	.789

a. EGYPT OR UK SAMPLE = EGYPT

b. Design: Intercept

Within Subjects Design: Fractal

c. Exact statistic

Mauchly's Test of Sphericity[a,b]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[c]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Fractal	.509	132.617	35	.000	.856	.890	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. EGYPT OR UK SAMPLE = EGYPT

b. Design: Intercept

Within Subjects Design: Fractal

c. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects[a]

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Fractal	Sphericity Assumed	3105.381	8	388.173	159.774	.000	.445
	Greenhouse-Geisser	3105.381	6.848	453.488	159.774	.000	.445
	Huynh-Feldt	3105.381	7.117	436.331	159.774	.000	.445
	Lower-bound	3105.381	1.000	3105.381	159.774	.000	.445
Error(Fractal)	Sphericity Assumed	3867.786	1592	2.430			
	Greenhouse-Geisser	3867.786	1362.706	2.838			
	Huynh-Feldt	3867.786	1416.290	2.731			
	Lower-bound	3867.786	199.000	19.436			

a. EGYPT OR UK SAMPLE = EGYPT

Tests of Within-Subjects Contrasts[a]

Measure: MEASURE_1

Source	Fractal	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Fractal	Linear	3021.037	1	3021.037	715.822	.000	.782
	Quadratic	15.986	1	15.986	5.566	.019	.027
	Cubic	15.984	1	15.984	6.450	.012	.031
	Order 4	44.329	1	44.329	19.846	.000	.091
	Order 5	3.962	1	3.962	1.879	.172	.009
	Order 6	2.105	1	2.105	1.332	.250	.007
	Order 7	1.309	1	1.309	.736	.392	.004
	Order 8	.669	1	.669	.309	.579	.002
Error(Fractal)	Linear	839.855	199	4.220			
	Quadratic	571.506	199	2.872			
	Cubic	493.176	199	2.478			
	Order 4	444.493	199	2.234			
	Order 5	419.626	199	2.109			
	Order 6	314.372	199	1.580			
	Order 7	353.800	199	1.778			
	Order 8	430.958	199	2.166			

a. EGYPT OR UK SAMPLE = EGYPT

Tests of Between-Subjects Effects[a]

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	30188.340	1	30188.340	5195.689	.000	.963
Error	1156.243	199	5.810			

a. EGYPT OR UK SAMPLE = EGYPT

Estimated Marginal Means

Fractal

Estimates[a]

Measure: MEASURE_1

Fractal	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1	5.993	.133	5.730	6.255
2	5.360	.130	5.103	5.617

3	5.143	.123	4.899	5.386
4	4.910	.124	4.665	5.155
5	4.403	.120	4.165	4.640
6	3.705	.116	3.477	3.933
7	2.773	.105	2.566	2.979
8	2.400	.101	2.200	2.600
9	2.173	.109	1.958	2.387

a. EGYPT OR UK SAMPLE = EGYPT

Pairwise Comparisons[a]

Measure: MEASURE_1

(I) Fractal	(J) Fractal	Mean Difference (I-J)	Std. Error	Sig.[c]	95% Confidence Interval for Difference[c]	
					Lower Bound	Upper Bound
1	2	.632*	.169	.008	.086	1.179
	3	.850*	.166	.000	.313	1.387
	4	1.082*	.151	.000	.592	1.573
	5	1.590*	.163	.000	1.062	2.118
	6	2.287*	.172	.000	1.731	2.844
	7	3.220*	.164	.000	2.687	3.753
	8	3.593*	.166	.000	3.053	4.132
	9	3.820*	.175	.000	3.254	4.386
2	1	-.632*	.169	.008	-1.179	-.086
	3	.218	.145	1.000	-.254	.689
	4	.450	.152	.126	-.044	.944
	5	.958*	.178	.000	.380	1.535
	6	1.655*	.167	.000	1.114	2.196
	7	2.588*	.169	.000	2.039	3.136
	8	2.960*	.167	.000	2.419	3.501
	9	3.188*	.170	.000	2.637	3.738
3	1	-.850*	.166	.000	-1.387	-.313
	2	-.218	.145	1.000	-.689	.254
	4	.232	.142	1.000	-.229	.694
	5	.740*	.157	.000	.232	1.248
	6	1.438*	.152	.000	.944	1.931
	7	2.370*	.159	.000	1.854	2.886
	8	2.743*	.153	.000	2.246	3.239
	9	2.970*	.162	.000	2.444	3.496
4	1	-1.082*	.151	.000	-1.573	-.592
	2	-.450	.152	.126	-.944	.044

	3	-.232	.142	1.000	-.694	.229
	5	.508*	.143	.017	.045	.970
	6	1.205*	.149	.000	.722	1.688
	7	2.138*	.155	.000	1.635	2.640
	8	2.510*	.143	.000	2.046	2.974
	9	2.738*	.171	.000	2.182	3.293
5	1	-1.590*	.163	.000	-2.118	-1.062
	2	-.958*	.178	.000	-1.535	-.380
	3	-.740*	.157	.000	-1.248	-.232
	4	-.508*	.143	.017	-.970	-.045
	6	.697*	.156	.000	.192	1.203
	7	1.630*	.145	.000	1.160	2.100
	8	2.003*	.156	.000	1.498	2.507
	9	2.230*	.168	.000	1.685	2.775
6	1	-2.287*	.172	.000	-2.844	-1.731
	2	-1.655*	.167	.000	-2.196	-1.114
	3	-1.438*	.152	.000	-1.931	-.944
	4	-1.205*	.149	.000	-1.688	-.722
	5	-.697*	.156	.000	-1.203	-.192
	7	.933*	.134	.000	.499	1.366
	8	1.305*	.135	.000	.867	1.743
	9	1.533*	.153	.000	1.037	2.028
7	1	-3.220*	.164	.000	-3.753	-2.687
	2	-2.588*	.169	.000	-3.136	-2.039
	3	-2.370*	.159	.000	-2.886	-1.854
	4	-2.138*	.155	.000	-2.640	-1.635
	5	-1.630*	.145	.000	-2.100	-1.160
	6	-.933*	.134	.000	-1.366	-.499
	8	.373	.123	.100	-.026	.771
	9	.600*	.141	.001	.144	1.056
8	1	-3.593*	.166	.000	-4.132	-3.053
	2	-2.960*	.167	.000	-3.501	-2.419
	3	-2.743*	.153	.000	-3.239	-2.246
	4	-2.510*	.143	.000	-2.974	-2.046
	5	-2.003*	.156	.000	-2.507	-1.498
	6	-1.305*	.135	.000	-1.743	-.867
	7	-.373	.123	.100	-.771	.026
	9	.228	.118	1.000	-.155	.610
9	1	-3.820*	.175	.000	-4.386	-3.254
	2	-3.188*	.170	.000	-3.738	-2.637

3	-2.970*	.162	.000	-3.496	-2.444
4	-2.738*	.171	.000	-3.293	-2.182
5	-2.230*	.168	.000	-2.775	-1.685
6	-1.533*	.153	.000	-2.028	-1.037
7	-.600*	.141	.001	-1.056	-.144
8	-.228	.118	1.000	-.610	.155

Based on estimated marginal means

*. The mean difference is significant at the

a. EGYPT OR UK SAMPLE = EGYPT

c. Adjustment for multiple comparisons: Bonferroni.

Multivariate Tests[a]

	Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Pillai's trace	.789	89.576[b]	8.000	192.000	.000	.7
Wilks' lambda	.211	89.576[b]	8.000	192.000	.000	.7
Hotelling's trace	3.732	89.576[b]	8.000	192.000	.000	.7
Roy's largest root	3.732	89.576[b]	8.000	192.000	.000	.7

Each F tests the multivariate effect of Fractal. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. EGYPT OR UK SAMPLE = EGYPT

b. Exact statistic

Descriptive Statistics[a]

	N	Minimum	Maximum	Mean	Std. Deviation
1.1	154	.00	10.00	4.5714	2.41755
1.2	154	.00	9.50	4.5487	2.10257
1.3	154	.00	9.00	4.6331	1.89430
1.4	154	.00	10.00	4.6266	1.87219
1.5	154	.00	9.00	4.6006	1.89114
1.6	154	.00	8.00	4.2890	1.90783
1.7	154	.00	9.00	4.2630	2.29392
1.8	154	.00	10.00	4.3149	2.60965
1.9	154	.00	10.00	4.3799	2.91943
Valid N (listwise)	154				

a. EGYPT OR UK SAMPLE = UK

EGYPT OR UK SAMPLE = UK

Descriptive Statistics[a]

	Mean	Std. Deviation	N

1.1	4.5714	2.41755	154
1.2	4.5487	2.10257	154
1.3	4.6331	1.89430	154
1.4	4.6266	1.87219	154
1.5	4.6006	1.89114	154
1.6	4.2890	1.90783	154
1.7	4.2630	2.29392	154
1.8	4.3149	2.60965	154
1.9	4.3799	2.91943	154

a. EGYPT OR UK SAMPLE = UK

Multivariate Tests[a,b]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Fractal	Pillai's Trace	.059	1.153[c]	8.000	146.000	.332	.059
	Wilks' Lambda	.941	1.153[c]	8.000	146.000	.332	.059
	Hotelling's Trace	.063	1.153[c]	8.000	146.000	.332	.059
	Roy's Largest Root	.063	1.153[c]	8.000	146.000	.332	.059

a. EGYPT OR UK SAMPLE = UK

b. Design: Intercept

Within Subjects Design: Fractal

c. Exact statistic

Mauchly's Test of Sphericity[a,b]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[c]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Fractal	.002	902.981	35	.000	.259	.262	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. EGYPT OR UK SAMPLE = UK

b. Design: Intercept

Within Subjects Design: Fractal

c. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects[a]

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Fractal	Sphericity Assumed	29.643	8	3.705	.954	.471	.006
	Greenhouse-Geisser	29.643	2.069	14.330	.954	.389	.006
	Huynh-Feldt	29.643	2.097	14.133	.954	.390	.006
	Lower-bound	29.643	1.000	29.643	.954	.330	.006
Error(Fractal)	Sphericity Assumed	4754.746	1224	3.885			
	Greenhouse-Geisser	4754.746	316.500	15.023			
	Huynh-Feldt	4754.746	320.907	14.817			
	Lower-bound	4754.746	153.000	31.077			

a. EGYPT OR UK SAMPLE = UK

Tests of Within-Subjects Contrasts[a]

Measure: MEASURE_1

Source	Fractal	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Fractal	Linear	16.630	1	16.630	.793	.375	.005
	Quadratic	.237	1	.237	.085	.772	.001
	Cubic	7.204	1	7.204	5.383	.022	.034
	Order 4	1.473	1	1.473	1.325	.252	.009
	Order 5	2.424	1	2.424	2.079	.151	.013
	Order 6	.397	1	.397	.374	.542	.002
	Order 7	.103	1	.103	.101	.751	.001
	Order 8	1.174	1	1.174	.726	.395	.005
Error(Fractal)	Linear	3207.961	153	20.967			
	Quadratic	428.769	153	2.802			
	Cubic	204.754	153	1.338			
	Order 4	170.194	153	1.112			
	Order 5	178.419	153	1.166			
	Order 6	162.398	153	1.061			
	Order 7	154.880	153	1.012			
	Order 8	247.370	153	1.617			

a. EGYPT OR UK SAMPLE = UK

Tests of Between-Subjects Effects[a]

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	27689.773	1	27689.773	1964.689	.000	.928
Error	2156.338	153	14.094			

a. EGYPT OR UK SAMPLE = UK

Estimated Marginal Means
Fractal

Estimates[a]

Measure: MEASURE_1

Fractal	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1	4.571	.195	4.187	4.956
2	4.549	.169	4.214	4.883
3	4.633	.153	4.332	4.935
4	4.627	.151	4.329	4.925
5	4.601	.152	4.300	4.902
6	4.289	.154	3.985	4.593
7	4.263	.185	3.898	4.628
8	4.315	.210	3.899	4.730
9	4.380	.235	3.915	4.845

a. EGYPT OR UK SAMPLE = UK

Pairwise Comparisons[a]

Measure: MEASURE_1

(I) Fractal	(J) Fractal	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	.023	.127	1.000	-.390	.436
	3	-.062	.144	1.000	-.532	.409
	4	-.055	.177	1.000	-.632	.521
	5	-.029	.208	1.000	-.708	.649
	6	.282	.262	1.000	-.570	1.135
	7	.308	.309	1.000	-.698	1.315
	8	.256	.347	1.000	-.873	1.386
	9	.192	.372	1.000	-1.021	1.404
2	1	-.023	.127	1.000	-.436	.390

	3	-.084	.123	1.000	-.485	.316
	4	-.078	.143	1.000	-.542	.386
	5	-.052	.179	1.000	-.634	.530
	6	.260	.222	1.000	-.462	.981
	7	.286	.275	1.000	-.609	1.180
	8	.234	.311	1.000	-.780	1.248
	9	.169	.341	1.000	-.943	1.280
3	1	.062	.144	1.000	-.409	.532
	2	.084	.123	1.000	-.316	.485
	4	.006	.124	1.000	-.396	.409
	5	.032	.138	1.000	-.418	.483
	6	.344	.188	1.000	-.269	.958
	7	.370	.237	1.000	-.401	1.141
	8	.318	.279	1.000	-.589	1.225
	9	.253	.308	1.000	-.750	1.257
4	1	.055	.177	1.000	-.521	.632
	2	.078	.143	1.000	-.386	.542
	3	-.006	.124	1.000	-.409	.396
	5	.026	.142	1.000	-.436	.488
	6	.338	.162	1.000	-.190	.865
	7	.364	.218	1.000	-.346	1.073
	8	.312	.248	1.000	-.495	1.118
	9	.247	.283	1.000	-.675	1.169
5	1	.029	.208	1.000	-.649	.708
	2	.052	.179	1.000	-.530	.634
	3	-.032	.138	1.000	-.483	.418
	4	-.026	.142	1.000	-.488	.436
	6	.312	.147	1.000	-.166	.789
	7	.338	.179	1.000	-.247	.922
	8	.286	.229	1.000	-.461	1.032
	9	.221	.262	1.000	-.631	1.073
6	1	-.282	.262	1.000	-1.135	.570
	2	-.260	.222	1.000	-.981	.462
	3	-.344	.188	1.000	-.958	.269
	4	-.338	.162	1.000	-.865	.190
	5	-.312	.147	1.000	-.789	.166
	7	.026	.147	1.000	-.453	.505
	8	-.026	.179	1.000	-.608	.556
	9	-.091	.214	1.000	-.787	.605
7	1	-.308	.309	1.000	-1.315	.698
	2	-.286	.275	1.000	-1.180	.609

	3	-.370	.237	1.000	-1.141	.401
	4	-.364	.218	1.000	-1.073	.346
	5	-.338	.179	1.000	-.922	.247
	6	-.026	.147	1.000	-.505	.453
	8	-.052	.150	1.000	-.539	.436
	9	-.117	.176	1.000	-.689	.455
8	1	-.256	.347	1.000	-1.386	.873
	2	-.234	.311	1.000	-1.248	.780
	3	-.318	.279	1.000	-1.225	.589
	4	-.312	.248	1.000	-1.118	.495
	5	-.286	.229	1.000	-1.032	.461
	6	.026	.179	1.000	-.556	.608
	7	.052	.150	1.000	-.436	.539
	9	-.065	.122	1.000	-.462	.332
9	1	-.192	.372	1.000	-1.404	1.021
	2	-.169	.341	1.000	-1.280	.943
	3	-.253	.308	1.000	-1.257	.750
	4	-.247	.283	1.000	-1.169	.675
	5	-.221	.262	1.000	-1.073	.631
	6	.091	.214	1.000	-.605	.787
	7	.117	.176	1.000	-.455	.689
	8	.065	.122	1.000	-.332	.462

Based on estimated marginal means

a. EGYPT OR UK SAMPLE = UK

b. Adjustment for multiple comparisons: Bonferroni.

Multivariate Tests[a]

	Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Pillai's trace	.059	1.153[b]	8.000	146.000	.332	.059
Wilks' lambda	.941	1.153[b]	8.000	146.000	.332	.059
Hotelling's trace	.063	1.153[b]	8.000	146.000	.332	.059
Roy's largest root	.063	1.153[b]	8.000	146.000	.332	.059

Each F tests the multivariate effect of Fractal. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. EGYPT OR UK SAMPLE = UK

b. Exact statistic

Univariate Tests

Measure: MEASURE_1

	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Contrast	33.032	1	33.032	5.614	.018	.016
Error	2071.057	352	5.884			

The F tests the effect of EGYPT OR UK SAMPLE. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

2. FractalLevel

Estimates

Measure: MEASURE_1

FractalLevel	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	11.866	.209	11.455	12.276
2	10.602	.178	10.252	10.952
3	7.967	.216	7.542	8.392

Pairwise Comparisons

Measure: MEASURE_1

(I) FractalLevel	(J) FractalLevel	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	95% Confidence Interval for Difference[b] Upper Bound
1	2	1.263*	.205	.000	.769	1.758
	3	3.898*	.339	.000	3.084	4.713
2	1	-1.263*	.205	.000	-1.758	-.769
	3	2.635*	.239	.000	2.061	3.209
3	1	-3.898*	.339	.000	-4.713	-3.084
	2	-2.635*	.239	.000	-3.209	-2.061

Based on estimated marginal means

*. The mean difference is significant at the

b. Adjustment for multiple comparisons: Bonferroni.

Multivariate Tests

	Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Pillai's trace	.287	70.695[a]	2.000	351.000	.000	.287
Wilks' lambda	.713	70.695[a]	2.000	351.000	.000	.287
Hotelling's trace	.403	70.695[a]	2.000	351.000	.000	.287
Roy's largest root	.403	70.695[a]	2.000	351.000	.000	.287

Each F tests the multivariate effect of FractalLevel. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.
a. Exact statistic

General Linear Model

Descriptive Statistics

	EGYPT OR UK SAMPLE	Mean	Std. Deviation	N
Low	EGYPT	13.0667	3.09910	200
	UK	10.6645	4.73483	154
	Total	12.0217	4.06860	354
Mid	EGYPT	10.5475	2.98008	200
	UK	10.6569	3.71523	154
	Total	10.5951	3.31542	354
High	EGYPT	5.8967	2.54400	200
	UK	10.0379	5.38512	154
	Total	7.6982	4.52157	354

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
FractalLevel	Pillai's Trace	.287	70.695[b]	2.000	351.000	.000	.287
	Wilks' Lambda	.713	70.695[b]	2.000	351.000	.000	.287
	Hotelling's Trace	.403	70.695[b]	2.000	351.000	.000	.287
	Roy's Largest Root	.403	70.695[b]	2.000	351.000	.000	.287
FractalLevel * EthGr	Pillai's Trace	.212	47.228[b]	2.000	351.000	.000	.212
	Wilks' Lambda	.788	47.228[b]	2.000	351.000	.000	.212
	Hotelling's Trace	.269	47.228[b]	2.000	351.000	.000	.212
	Roy's Largest Root	.269	47.228[b]	2.000	351.000	.000	.212

a. Design: Intercept + EthGr
Within Subjects Design: FractalLevel
b. Exact statistic

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b] Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FractalLevel	.614	171.043	2	.000	.722	.726	.500

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + EthGr

Within Subjects Design: FractalLevel

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
FractalLevel	Sphericity Assumed	2753.538	2	1376.769	110.997	.000	.240
	Greenhouse-Geisser	2753.538	1.443	1907.815	110.997	.000	.240
	Huynh-Feldt	2753.538	1.452	1896.683	110.997	.000	.240
	Lower-bound	2753.538	1.000	2753.538	110.997	.000	.240
FractalLevel * EthGr	Sphericity Assumed	1896.119	2	948.059	76.434	.000	.178
	Greenhouse-Geisser	1896.119	1.443	1313.744	76.434	.000	.178
	Huynh-Feldt	1896.119	1.452	1306.078	76.434	.000	.178
	Lower-bound	1896.119	1.000	1896.119	76.434	.000	.178
Error(FractalLevel)	Sphericity Assumed	8732.145	704	12.404			
	Greenhouse-Geisser	8732.145	508.039	17.188			
	Huynh-Feldt	8732.145	511.021	17.088			
	Lower-bound	8732.145	352.000	24.807			

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	FractalLevel	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
FractalLevel	Linear	2644.421	1	2644.421	132.455	.000	.273
	Quadratic	109.117	1	109.117	22.533	.000	.060
FractalLevel * EthGr	Linear	1862.607	1	1862.607	93.295	.000	.210
	Quadratic	33.512	1	33.512	6.920	.009	.019
Error(FractalLevel)	Linear	7027.556	352	19.965			
	Quadratic	1704.589	352	4.843			

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	107457.025	1	107457.025	6087.854	.000	.945
EthGr	99.095	1	99.095	5.614	.018	.016
Error	6213.171	352	17.651			

Estimated Marginal Means
1. EGYPT OR UK SAMPLE

Estimates

Measure: MEASURE_1

EGYPT OR UK SAMPLE	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
EGYPT	9.837	.172	9.500	10.174
UK	10.453	.195	10.069	10.838

Pairwise Comparisons

Measure: MEASURE_1

(I) EGYPT OR UK SAMPLE	(J) EGYPT OR UK SAMPLE	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
EGYPT	UK	-.616*	.260	.018	-1.128	-.105
UK	EGYPT	.616*	.260	.018	.105	1.128

Based on estimated marginal means

*. The mean difference is significant at the

b. Adjustment for multiple comparisons: Bonferroni.

General Linear Model

Descriptive Statistics

	GENDER	Mean	Std. Deviation	N
Low	M	12.3843	2.54022	121
	F	11.8191	4.64960	222
	Total	12.0185	4.03823	343
Mid	M	9.4986	2.75029	121
	F	11.2342	3.39741	222
	Total	10.6220	3.28673	343
High	M	5.7521	2.64322	121
	F	8.8296	4.93552	222
	Total	7.7439	4.51234	343

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
FractalLevel	Pillai's Trace	.314	77.754[b]	2.000	340.000	.000	.314
	Wilks' Lambda	.686	77.754[b]	2.000	340.000	.000	.314
	Hotelling's Trace	.457	77.754[b]	2.000	340.000	.000	.314
	Roy's Largest Root	.457	77.754[b]	2.000	340.000	.000	.314
FractalLevel * GENDER	Pillai's Trace	.079	14.546[b]	2.000	340.000	.000	.079
	Wilks' Lambda	.921	14.546[b]	2.000	340.000	.000	.079
	Hotelling's Trace	.086	14.546[b]	2.000	340.000	.000	.079
	Roy's Largest Root	.086	14.546[b]	2.000	340.000	.000	.079

a. Design: Intercept + GENDER

Within Subjects Design: FractalLevel

b. Exact statistic

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within	Mauchly's	Approx.	df	Sig.	Epsilon[b]

Subjects Effect	W	Chi-Square			Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FractalLevel	.540	209.636	2	.000	.685	.689	.500

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + GENDER
Within Subjects Design: FractalLevel

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
FractalLevel	Sphericity Assumed	3718.895	2	1859.448	130.267	.000	.276
	Greenhouse-Geisser	3718.895	1.370	2715.185	130.267	.000	.276
	Huynh-Feldt	3718.895	1.377	2700.005	130.267	.000	.276
	Lower-bound	3718.895	1.000	3718.895	130.267	.000	.276
FractalLevel * GENDER	Sphericity Assumed	531.605	2	265.802	18.621	.000	.052
	Greenhouse-Geisser	531.605	1.370	388.128	18.621	.000	.052
	Huynh-Feldt	531.605	1.377	385.958	18.621	.000	.052
	Lower-bound	531.605	1.000	531.605	18.621	.000	.052
Error(FractalLevel)	Sphericity Assumed	9734.973	682	14.274			
	Greenhouse-Geisser	9734.973	467.056	20.843			
	Huynh-Feldt	9734.973	469.682	20.727			
	Lower-bound	9734.973	341.000	28.548			

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	FractalLevel	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
FractalLevel	Linear	3625.098	1	3625.098	153.267	.000	.310

	Quadratic	93.797	1	93.797	19.157	.000	.053
FractalLevel * GENDER	Linear	519.602	1	519.602	21.969	.000	.061
	Quadratic	12.003	1	12.003	2.451	.118	.007
Error(FractalLevel)	Linear	8065.374	341	23.652			
	Quadratic	1669.598	341	4.896			

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	92473.590	1	92473.590	5735.979	.000	.944
GENDER	471.054	1	471.054	29.219	.000	.079
Error	5497.491	341	16.122			

Estimated Marginal Means

1. FractalLevel

Estimates

Measure: MEASURE_1

FractalLevel	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1	12.102	.228	11.653	12.550
2	10.366	.180	10.013	10.720
3	7.291	.241	6.816	7.766

Pairwise Comparisons

Measure: MEASURE_1

(I) FractalLevel	(J) FractalLevel	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	1.735*	.219	.000	1.209	2.262
	3	4.811*	.389	.000	3.876	5.746
2	1	-1.735*	.219	.000	-2.262	-1.209
	3	3.076*	.273	.000	2.419	3.732
3	1	-4.811*	.389	.000	-5.746	-3.876
	2	-3.076*	.273	.000	-3.732	-2.419

Based on estimated marginal means

*. The mean difference is significant at the

b. Adjustment for multiple comparisons: Bonferroni.

Multivariate Tests

	Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Pillai's trace	.314	77.754[a]	2.000	340.000	.000	.314
Wilks' lambda	.686	77.754[a]	2.000	340.000	.000	.314
Hotelling's trace	.457	77.754[a]	2.000	340.000	.000	.314
Roy's largest root	.457	77.754[a]	2.000	340.000	.000	.314

Each F tests the multivariate effect of FractalLevel. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

2. GENDER

Estimates

Measure: MEASURE_1

GENDER	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
M	9.212	.211	8.797	9.626
F	10.628	.156	10.322	10.934

Pairwise Comparisons

Measure: MEASURE_1

(I) GENDER	(J) GENDER	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
M	F	-1.416*	.262	.000	-1.931	-.901
F	M	1.416*	.262	.000	.901	1.931

Based on estimated marginal means

*. The mean difference is significant at the

b. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Measure: MEASURE_1

	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Contrast	157.018	1	157.018	29.219	.000	.079
Error	1832.497	341	5.374			

The F tests the effect of GENDER. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

General Linear Model

Between-Subjects Factors

		Value Label	N
AgeCategory	1.00	20yrs or Below	238
	2.00	21yrs +	116

Descriptive Statistics

	AgeCategory	Mean	Std. Deviation	N
Low	20yrs or Below	12.1261	3.74732	238
	21yrs +	11.8075	4.66944	116
	Total	12.0217	4.06860	354
Mid	20yrs or Below	10.5819	3.23098	238
	21yrs +	10.6221	3.49654	116
	Total	10.5951	3.31542	354
High	20yrs or Below	7.2794	4.30326	238
	21yrs +	8.5575	4.84614	116
	Total	7.6982	4.52157	354

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
FractalLevel	Pillai's Trace	.235	53.959[b]	2.000	351.000	.000	.235
	Wilks' Lambda	.765	53.959[b]	2.000	351.000	.000	.235
	Hotelling's Trace	.307	53.959[b]	2.000	351.000	.000	.235
	Roy's Largest Root	.307	53.959[b]	2.000	351.000	.000	.235
FractalLevel * AgeCategory	Pillai's Trace	.014	2.558[b]	2.000	351.000	.079	.014
	Wilks' Lambda	.986	2.558[b]	2.000	351.000	.079	.014
	Hotelling's Trace	.015	2.558[b]	2.000	351.000	.079	.014
	Roy's Largest Root	.015	2.558[b]	2.000	351.000	.079	.014

a. Design: Intercept + AgeCategory

Within Subjects Design: FractalLevel

b. Exact statistic

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b] Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FractalLevel	.530	223.155	2	.000	.680	.684	.500

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + AgeCategory
Within Subjects Design: FractalLevel

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
FractalLevel	Sphericity Assumed	2646.731	2	1323.366	88.570	.000	.201
	Greenhouse-Geisser	2646.731	1.360	1945.972	88.570	.000	.201
	Huynh-Feldt	2646.731	1.367	1935.541	88.570	.000	.201
	Lower-bound	2646.731	1.000	2646.731	88.570	.000	.201
FractalLevel * AgeCategory	Sphericity Assumed	109.452	2	54.726	3.663	.026	.010
	Greenhouse-Geisser	109.452	1.360	80.473	3.663	.043	.010
	Huynh-Feldt	109.452	1.367	80.041	3.663	.043	.010
	Lower-bound	109.452	1.000	109.452	3.663	.056	.010
Error(FractalLevel)	Sphericity Assumed	10518.813	704	14.941			
	Greenhouse-Geisser	10518.813	478.758	21.971			
	Huynh-Feldt	10518.813	481.338	21.853			
	Lower-bound	10518.813	352.000	29.883			

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	FractalLevel	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared

FractalLevel	Linear	2556.296	1	2556.296	102.359	.000	.225
	Quadratic	90.435	1	90.435	18.421	.000	.050
FractalLevel * AgeCategory	Linear	99.407	1	99.407	3.980	.047	.011
	Quadratic	10.045	1	10.045	2.046	.153	.006
Error(FractalLevel)	Linear	8790.757	352	24.974			
	Quadratic	1728.056	352	4.909			

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	96651.013	1	96651.013	5411.964	.000	.939
AgeCategory	25.979	1	25.979	1.455	.229	.004
Error	6286.286	352	17.859			

Estimated Marginal Means

AgeCategory

Estimates

Measure: MEASURE_1

AgeCategory	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
20yrs or Below	9.996	.158	9.685	10.307
21yrs +	10.329	.227	9.883	10.775

Pairwise Comparisons

Measure: MEASURE_1

(I) AgeCategory	(J) AgeCategory	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
20yrs or Below	21yrs +	-.333	.276	.229	-.877	.210
21yrs +	20yrs or Below	.333	.276	.229	-.210	.877

Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

Chapter 9 Output:

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

Flevels	Dependent Variable
1	D1.1
2	D1.2
3	D1.3
4	D1.4
5	D1.5
6	D1.6
7	D1.7
8	D1.8
9	D1.9

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Flevels	Pillai's Trace	.227	10.406[b]	8.000	283.000	.000
	Wilks' Lambda	.773	10.406[b]	8.000	283.000	.000
	Hotelling's Trace	.294	10.406[b]	8.000	283.000	.000
	Roy's Largest Root	.294	10.406[b]	8.000	283.000	.000

a. Design: Intercept
Within Subjects Design: Flevels

b. Exact statistic

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Flevels	.000	2979.156	35	.000	.183	.184	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept
Within Subjects Design: Flevels

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
Flevels	Sphericity Assumed	2270.580	8	283.823	23.859	.000
	Greenhouse-Geisser	2270.580	1.464	1551.355	23.859	.000
	Huynh-Feldt	2270.580	1.469	1545.479	23.859	.000
	Lower-bound	2270.580	1.000	2270.580	23.859	.000
Error(Flevels)	Sphericity Assumed	27598.086	2320	11.896		
	Greenhouse-Geisser	27598.086	424.447	65.021		
	Huynh-Feldt	27598.086	426.061	64.775		
	Lower-bound	27598.086	290.000	95.166		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	Flevels	Type III Sum of Squares	df	Mean Square	F	Sig.
Flevels	Linear	1904.828	1	1904.828	25.751	.000
	Quadratic	181.353	1	181.353	36.198	.000
	Cubic	120.748	1	120.748	33.639	.000
	Order 4	20.907	1	20.907	8.373	.004
	Order 5	17.121	1	17.121	7.847	.005
	Order 6	3.475	1	3.475	1.725	.190
	Order 7	11.684	1	11.684	2.978	.085
	Order 8	10.464	1	10.464	5.285	.022
Error(Flevels)	Linear	21451.289	290	73.970		
	Quadratic	1452.912	290	5.010		
	Cubic	1040.951	290	3.589		
	Order 4	724.149	290	2.497		
	Order 5	632.723	290	2.182		
	Order 6	584.278	290	2.015		

	Order 7	1137.656	290	3.923		
	Order 8	574.129	290	1.980		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	94512.138	1	94512.138	1930790.086	.000
Error	14.195	290	.049		

Estimated Marginal Means
Flevels

Estimates

Measure: MEASURE_1

Flevels	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1	6.656	.226	6.212	7.101
2	7.048	.229	6.597	7.499
3	6.938	.211	6.522	7.354
4	6.725	.100	6.529	6.921
5	6.347	.100	6.150	6.544
6	6.089	.102	5.889	6.289
7	4.983	.204	4.581	5.384
8	4.615	.227	4.168	5.062
9	4.663	.235	4.200	5.126

Pairwise Comparisons

Measure: MEASURE_1

(I) Flevels	(J) Flevels	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	-.392*	.104	.007	-.728	-.056
	3	-.282	.109	.358	-.632	.069
	4	-.069	.230	1.000	-.811	.673
	5	.309	.255	1.000	-.513	1.132
	6	.567	.287	1.000	-.358	1.492
	7	1.674*	.415	.003	.333	3.014
	8	2.041*	.440	.000	.619	3.463
	9	1.993*	.445	.000	.556	3.431
2	1	.392*	.104	.007	.056	.728

	3	.110	.115	1.000	-.260	.480
	4	.323	.233	1.000	-.428	1.074
	5	.701	.258	.252	-.132	1.534
	6	.959*	.287	.034	.032	1.886
	7	2.065*	.420	.000	.709	3.421
	8	2.433*	.444	.000	1.001	3.865
	9	2.385*	.447	.000	.941	3.829
3	1	.282	.109	.358	-.069	.632
	2	-.110	.115	1.000	-.480	.260
	4	.213	.215	1.000	-.480	.906
	5	.591	.238	.492	-.178	1.360
	6	.849	.267	.059	-.013	1.710
	7	1.955*	.402	.000	.658	3.252
	8	2.323*	.427	.000	.946	3.700
	9	2.275*	.432	.000	.881	3.669
4	1	.069	.230	1.000	-.673	.811
	2	-.323	.233	1.000	-1.074	.428
	3	-.213	.215	1.000	-.906	.480
	5	.378	.122	.074	-.014	.770
	6	.636*	.136	.000	.198	1.073
	7	1.742*	.255	.000	.918	2.566
	8	2.110*	.280	.000	1.207	3.013
	9	2.062*	.293	.000	1.118	3.006
5	1	-.309	.255	1.000	-1.132	.513
	2	-.701	.258	.252	-1.534	.132
	3	-.591	.238	.492	-1.360	.178
	4	-.378	.122	.074	-.770	.014
	6	.258	.119	1.000	-.125	.640
	7	1.364*	.239	.000	.594	2.134
	8	1.732*	.262	.000	.888	2.576
	9	1.684*	.273	.000	.803	2.565
6	1	-.567	.287	1.000	-1.492	.358
	2	-.959*	.287	.034	-1.886	-.032
	3	-.849	.267	.059	-1.710	.013
	4	-.636*	.136	.000	-1.073	-.198
	5	-.258	.119	1.000	-.640	.125
	7	1.107*	.207	.000	.437	1.776
	8	1.474*	.225	.000	.748	2.201
	9	1.426*	.239	.000	.655	2.197
7	1	-1.674*	.415	.003	-3.014	-.333
	2	-2.065*	.420	.000	-3.421	-.709

	3	-1.955*	.402	.000	-3.252	-.658
	4	-1.742*	.255	.000	-2.566	-.918
	5	-1.364*	.239	.000	-2.134	-.594
	6	-1.107*	.207	.000	-1.776	-.437
	8	.368*	.108	.027	.019	.717
	9	.320	.120	.285	-.066	.705
8	1	-2.041*	.440	.000	-3.463	-.619
	2	-2.433*	.444	.000	-3.865	-1.001
	3	-2.323*	.427	.000	-3.700	-.946
	4	-2.110*	.280	.000	-3.013	-1.207
	5	-1.732*	.262	.000	-2.576	-.888
	6	-1.474*	.225	.000	-2.201	-.748
	7	-.368*	.108	.027	-.717	-.019
	9	-.048	.098	1.000	-.364	.268
9	1	-1.993*	.445	.000	-3.431	-.556
	2	-2.385*	.447	.000	-3.829	-.941
	3	-2.275*	.432	.000	-3.669	-.881
	4	-2.062*	.293	.000	-3.006	-1.118
	5	-1.684*	.273	.000	-2.565	-.803
	6	-1.426*	.239	.000	-2.197	-.655
	7	-.320	.120	.285	-.705	.066
	8	.048	.098	1.000	-.268	.364

Based on estimated marginal means

*. The mean difference is significant at the

b. Adjustment for multiple comparisons: Bonferroni.

Multivariate Tests

	Value	F	Hypothesis df	Error df	Sig.
Pillai's trace	.227	10.406[a]	8.000	283.000	.000
Wilks' lambda	.773	10.406[a]	8.000	283.000	.000
Hotelling's trace	.294	10.406[a]	8.000	283.000	.000
Roy's largest root	.294	10.406[a]	8.000	283.000	.000

Each F tests the multivariate effect of Flevels. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

General Linear Model

Multivariate Tests[a]

Effect	Value	F	Hypothesis df	Error df	Sig.

Flevels	Pillai's Trace	.227	10.377[b]	8.000	282.000	.000
	Wilks' Lambda	.773	10.377[b]	8.000	282.000	.000
	Hotelling's Trace	.294	10.377[b]	8.000	282.000	.000
	Roy's Largest Root	.294	10.377[b]	8.000	282.000	.000
Flevels * Gender	Pillai's Trace	.025	.905[b]	8.000	282.000	.513
	Wilks' Lambda	.975	.905[b]	8.000	282.000	.513
	Hotelling's Trace	.026	.905[b]	8.000	282.000	.513
	Roy's Largest Root	.026	.905[b]	8.000	282.000	.513

a. Design: Intercept + Gender
 Within Subjects Design: Flevels
b. Exact statistic

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Flevels	.000	2973.404	35	.000	.183	.184	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.
a. Design: Intercept + Gender
 Within Subjects Design: Flevels
b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
Flevels	Sphericity Assumed	2105.435	8	263.179	22.073	.000
	Greenhouse-Geisser	2105.435	1.462	1440.251	22.073	.000
	Huynh-Feldt	2105.435	1.472	1429.840	22.073	.000
	Lower-bound	2105.435	1.000	2105.435	22.073	.000

Flevels * Gender	Sphericity Assumed	31.675	8	3.959	.332	.954
	Greenhouse-Geisser	31.675	1.462	21.668	.332	.649
	Huynh-Feldt	31.675	1.472	21.511	.332	.650
	Lower-bound	31.675	1.000	31.675	.332	.565
Error(Flevels)	Sphericity Assumed	27566.411	2312	11.923		
	Greenhouse-Geisser	27566.411	422.475	65.250		
	Huynh-Feldt	27566.411	425.552	64.778		
	Lower-bound	27566.411	289.000	95.386		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	Flevels	Type III Sum of Squares	df	Mean Square	F	Sig.
Flevels	Linear	1732.895	1	1732.895	23.361	.000
	Quadratic	188.058	1	188.058	37.587	.000
	Cubic	116.830	1	116.830	32.444	.000
	Order 4	21.903	1	21.903	8.753	.003
	Order 5	15.381	1	15.381	7.028	.008
	Order 6	3.191	1	3.191	1.578	.210
	Order 7	12.431	1	12.431	3.160	.077
	Order 8	14.745	1	14.745	7.541	.006
Flevels * Gender	Linear	13.428	1	13.428	.181	.671
	Quadratic	6.984	1	6.984	1.396	.238
	Cubic	.252	1	.252	.070	.792
	Order 4	1.002	1	1.002	.400	.527
	Order 5	.207	1	.207	.095	.759
	Order 6	.015	1	.015	.007	.932
	Order 7	.751	1	.751	.191	.663
	Order 8	9.037	1	9.037	4.622	.032
Error(Flevels)	Linear	21437.861	289	74.179		
	Quadratic	1445.928	289	5.003		
	Cubic	1040.699	289	3.601		
	Order 4	723.147	289	2.502		
	Order 5	632.516	289	2.189		
	Order 6	584.263	289	2.022		
	Order 7	1136.906	289	3.934		

	Order 8	565.092	289	1.955		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	89516.850	1	89516.850	1823931.723	.000
Gender	.012	1	.012	.237	.627
Error	14.184	289	.049		

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

Flevels	Dependent Variable
1	D1.1
2	D1.2
3	D1.3
4	D1.4
5	D1.5
6	D1.6
7	D1.7
8	D1.8
9	D1.9

Between-Subjects Factors

		Value Label	N
AgeGrouping	1.00	18-20	30
	2.00	21-30	171
	3.00	31-40	60
	4.00	41-50	14
	5.00	51-60	12
	6.00	61-70	3
	7.00	71-80	1

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Flevels	Pillai's Trace	.023	.811[b]	8.000	277.000	.593

	Wilks' Lambda	.977	.811[b]	8.000	277.000	.593
	Hotelling's Trace	.023	.811[b]	8.000	277.000	.593
	Roy's Largest Root	.023	.811[b]	8.000	277.000	.593
Flevels * AgeGrouping	Pillai's Trace	.161	.971	48.000	1692.000	.529
	Wilks' Lambda	.848	.973	48.000	1367.018	.527
	Hotelling's Trace	.170	.974	48.000	1652.000	.525
	Roy's Largest Root	.079	2.771[c]	8.000	282.000	.006

a. Design: Intercept + AgeGrouping
Within Subjects Design: Flevels

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Flevels	.000	2856.082	35	.000	.185	.190	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + AgeGrouping
Within Subjects Design: Flevels

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
Flevels	Sphericity Assumed	74.846	8	9.356	.808	.596
	Greenhouse-Geisser	74.846	1.482	50.510	.808	.414
	Huynh-Feldt	74.846	1.519	49.266	.808	.416

	Lower-bound	74.846	1.000	74.846	.808	.370
Flevels * AgeGrouping	Sphericity Assumed	1285.468	48	26.781	2.312	.000
	Greenhouse-Geisser	1285.468	8.891	144.583	2.312	.016
	Huynh-Feldt	1285.468	9.115	141.022	2.312	.015
	Lower-bound	1285.468	6.000	214.245	2.312	.034
Error(Flevels)	Sphericity Assumed	26312.618	2272	11.581		
	Greenhouse-Geisser	26312.618	420.836	62.525		
	Huynh-Feldt	26312.618	431.459	60.985		
	Lower-bound	26312.618	284.000	92.650		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	Flevels	Type III Sum of Squares	df	Mean Square	F	Sig.
Flevels	Linear	42.064	1	42.064	.588	.444
	Quadratic	21.705	1	21.705	4.332	.038
	Cubic	1.919	1	1.919	.555	.457
	Order 4	6.163	1	6.163	2.444	.119
	Order 5	.174	1	.174	.080	.777
	Order 6	2.817	1	2.817	1.406	.237
	Order 7	.000	1	.000	.000	.992
	Order 8	.004	1	.004	.002	.965
Flevels * AgeGrouping	Linear	1122.876	6	187.146	2.615	.018
	Quadratic	29.841	6	4.974	.993	.430
	Cubic	58.494	6	9.749	2.818	.011
	Order 4	8.035	6	1.339	.531	.785
	Order 5	17.114	6	2.852	1.316	.250
	Order 6	15.116	6	2.519	1.257	.277
	Order 7	27.347	6	4.558	1.166	.325
	Order 8	6.645	6	1.107	.554	.767
Error(Flevels)	Linear	20328.413	284	71.579		
	Quadratic	1423.070	284	5.011		
	Cubic	982.456	284	3.459		
	Order 4	716.114	284	2.522		
	Order 5	615.609	284	2.168		

	Order 6	569.162	284	2.004		
	Order 7	1110.310	284	3.910		
	Order 8	567.484	284	1.998		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	10299.870	1	10299.870	207880.368	.000
AgeGrouping	.124	6	.021	.418	.867
Error	14.071	284	.050		

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

Flevels	Dependent Variable
1	D1.1
2	D1.2
3	D1.3
4	D1.4
5	D1.5
6	D1.6
7	D1.7
8	D1.8
9	D1.9

Between-Subjects Factors

		Value Label	N
NewLocationGroup	1.00	Europe	35
	2.00	North America	24
	3.00	Central Asia	195

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Flevels	Pillai's Trace	.151	5.405[b]	8.000	244.000	.000
	Wilks' Lambda	.849	5.405[b]	8.000	244.000	.000
	Hotelling's Trace	.177	5.405[b]	8.000	244.000	.000

	Roy's Largest Root	.177	5.405[b]	8.000	244.000	.000
Flevels * NewLocationGroup	Pillai's Trace	.109	1.761	16.000	490.000	.034
	Wilks' Lambda	.894	1.758[b]	16.000	488.000	.034
	Hotelling's Trace	.116	1.755	16.000	486.000	.034
	Roy's Largest Root	.075	2.296[c]	8.000	245.000	.022

a. Design: Intercept + NewLocationGroup
 Within Subjects Design: Flevels
b. Exact statistic
c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Flevels	.000	2445.295	35	.000	.187	.189	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.
a. Design: Intercept + NewLocationGroup
 Within Subjects Design: Flevels
b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
Flevels	Sphericity Assumed	509.195	8	63.649	5.749	.000
	Greenhouse-Geisser	509.195	1.492	341.217	5.749	.008
	Huynh-Feldt	509.195	1.511	336.960	5.749	.008
	Lower-bound	509.195	1.000	509.195	5.749	.017
Flevels * NewLocationGroup	Sphericity Assumed	881.348	16	55.084	4.976	.000

	Greenhouse-Geisser	881.348	2.985	295.300	4.976	.002
	Huynh-Feldt	881.348	3.022	291.616	4.976	.002
	Lower-bound	881.348	2.000	440.674	4.976	.008
Error(Flevels)	Sphericity Assumed	22229.911	2008	11.071		
	Greenhouse-Geisser	22229.911	374.565	59.349		
	Huynh-Feldt	22229.911	379.297	58.608		
	Lower-bound	22229.911	251.000	88.565		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	Flevels	Type III Sum of Squares	df	Mean Square	F	Sig.
Flevels	Linear	360.280	1	360.280	5.272	.022
	Quadratic	84.587	1	84.587	19.388	.000
	Cubic	47.464	1	47.464	13.474	.000
	Order 4	7.286	1	7.286	2.828	.094
	Order 5	4.228	1	4.228	1.955	.163
	Order 6	.043	1	.043	.021	.884
	Order 7	.646	1	.646	.179	.673
	Order 8	4.660	1	4.660	2.365	.125
Flevels * NewLocationGroup	Linear	806.837	2	403.419	5.904	.003
	Quadratic	5.887	2	2.943	.675	.510
	Cubic	7.584	2	3.792	1.076	.342
	Order 4	.904	2	.452	.175	.839
	Order 5	11.320	2	5.660	2.617	.075
	Order 6	9.420	2	4.710	2.326	.100
	Order 7	35.376	2	17.688	4.898	.008
	Order 8	4.020	2	2.010	1.020	.362
Error(Flevels)	Linear	17151.942	251	68.334		
	Quadratic	1095.073	251	4.363		
	Cubic	884.211	251	3.523		
	Order 4	646.659	251	2.576		
	Order 5	542.850	251	2.163		
	Order 6	508.170	251	2.025		
	Order 7	906.425	251	3.611		

Order 8	494.581	251	1.970		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	38664.092	1	38664.092	2275751.727	.000
NewLocationGroup	.016	2	.008	.471	.625
Error	4.264	251	.017		

Estimated Marginal Means
NewLocationGroup

Estimates

Measure: MEASURE_1

NewLocationGroup	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Europe	6.000	.007	5.986	6.014
North America	6.000	.009	5.983	6.017
Central Asia	5.994	.003	5.988	6.000

Pairwise Comparisons

Measure: MEASURE_1

(I) NewLocationGroup	(J) NewLocationGroup	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
Europe	North America	-3.886E-16	.012	1.000	-.028	.028
	Central Asia	.006	.008	1.000	-.013	.025
North America	Europe	3.886E-16	.012	1.000	-.028	.028
	Central Asia	.006	.009	1.000	-.016	.029
Central Asia	Europe	-.006	.008	1.000	-.025	.013
	North America	-.006	.009	1.000	-.029	.016

Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Measure: MEASURE_1

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	.002	2	.001	.471	.625
Error	.474	251	.002		

The F tests the effect of NewLocationGroup. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Chapter 10 Output:

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

FDlevel	Dependent Variable
1	FD11
2	FD12
3	FD13
4	FD14
5	FD15
6	FD16
7	FD17
8	FD18
9	FD19

Country = UK

Between-Subjects Factors[a]

a. Country = UK

Multivariate Tests[a,b]

Effect		Value	F	Hypothesis df	Error df	Sig.
FDlevel	Pillai's Trace	.181	1.078[c]	8.000	39.000	.398
	Wilks' Lambda	.819	1.078[c]	8.000	39.000	.398
	Hotelling's Trace	.221	1.078[c]	8.000	39.000	.398
	Roy's Largest Root	.221	1.078[c]	8.000	39.000	.398

a. Country = UK

b. Design: Intercept
Within Subjects Design: FDlevel
c. Exact statistic

Mauchly's Test of Sphericity[a,b]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[c]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FDlevel	.000	510.857	35	.000	.187	.191	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.
a. Country = UK
b. Design: Intercept
Within Subjects Design: FDlevel
c. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects[a]

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Sphericity Assumed	98.553	8	12.319	.970	.459
	Greenhouse-Geisser	98.553	1.493	66.008	.970	.362
	Huynh-Feldt	98.553	1.532	64.340	.970	.364
	Lower-bound	98.553	1.000	98.553	.970	.330
Error(FDlevel)	Sphericity Assumed	4675.447	368	12.705		
	Greenhouse-Geisser	4675.447	68.681	68.075		
	Huynh-Feldt	4675.447	70.461	66.355		
	Lower-bound	4675.447	46.000	101.640		

a. Country = UK

Tests of Within-Subjects Contrasts[a]

Measure: MEASURE_1

Source	FDlevel	Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Linear	5.993	1	5.993	.078	.782
	Quadratic	75.004	1	75.004	9.225	.004
	Cubic	.013	1	.013	.004	.951
	Order 4	12.789	1	12.789	4.938	.031
	Order 5	1.440	1	1.440	.635	.430
	Order 6	.650	1	.650	.325	.572
	Order 7	2.480E-5	1	2.480E-5	.000	.998
	Order 8	2.662	1	2.662	1.735	.194
Error(FDlevel)	Linear	3555.574	46	77.295		
	Quadratic	374.015	46	8.131		
	Cubic	161.905	46	3.520		
	Order 4	119.142	46	2.590		
	Order 5	104.367	46	2.269		
	Order 6	92.159	46	2.003		
	Order 7	197.707	46	4.298		
	Order 8	70.578	46	1.534		

a. Country = UK

Tests of Between-Subjects Effects[a]

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	15228.000	1	15228.000	3080778804470218200.000	.000
Error	2.274E-13	46	4.943E-15		

a. Country = UK

Country = Egypt

Multivariate Tests[a,b]

Effect		Value	F	Hypothesis df	Error df	Sig.
FDlevel	Pillai's Trace	.299	1.334[c]	8.000	25.000	.273
	Wilks' Lambda	.701	1.334[c]	8.000	25.000	.273
	Hotelling's Trace	.427	1.334[c]	8.000	25.000	.273
	Roy's Largest Root	.427	1.334[c]	8.000	25.000	.273

a. Country = Egypt

b. Design: Intercept
 Within Subjects Design: FDlevel
c. Exact statistic

Mauchly's Test of Sphericity[a,b]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[c]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FDlevel	.000	300.330	35	.000	.192	.200	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.
a. Country = Egypt
b. Design: Intercept
 Within Subjects Design: FDlevel
c. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects[a]

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Sphericity Assumed	77.333	8	9.667	.759	.639
	Greenhouse-Geisser	77.333	1.536	50.356	.759	.441
	Huynh-Feldt	77.333	1.598	48.397	.759	.446
	Lower-bound	77.333	1.000	77.333	.759	.390
Error(FDlevel)	Sphericity Assumed	3258.667	256	12.729		
	Greenhouse-Geisser	3258.667	49.143	66.310		
	Huynh-Feldt	3258.667	51.133	63.729		
	Lower-bound	3258.667	32.000	101.833		

a. Country = Egypt

Tests of Within-Subjects Contrasts[a]

Measure: MEASURE_1

Source	FDlevel	Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Linear	28.608	1	28.608	.378	.543
	Quadratic	21.365	1	21.365	3.175	.084
	Cubic	1.719	1	1.719	.509	.481
	Order 4	1.445	1	1.445	.636	.431
	Order 5	7.841	1	7.841	3.749	.062
	Order 6	1.607	1	1.607	.513	.479
	Order 7	.043	1	.043	.008	.928
	Order 8	14.704	1	14.704	4.451	.043
Error(FDlevel)	Linear	2423.292	32	75.728		
	Quadratic	215.356	32	6.730		
	Cubic	108.179	32	3.381		
	Order 4	72.666	32	2.271		
	Order 5	66.923	32	2.091		
	Order 6	100.148	32	3.130		
	Order 7	166.394	32	5.200		
	Order 8	105.709	32	3.303		

a. Country = Egypt

Tests of Between-Subjects Effects[a]

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	10692.000	1	10692.000	.	.
Error	.000	32	.000		

a. Country = Egypt

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

FDlevel	Dependent Variable
1	FD11
2	FD12
3	FD13
4	FD14
5	FD15
6	FD16
7	FD17

8	FD18
9	FD19

Between-Subjects Factors

		Value Label	N
Gender	1.0	male	28
	2.0	female	52

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
FDlevel	Pillai's Trace	.182	1.977[b]	8.000	71.000	.062
	Wilks' Lambda	.818	1.977[b]	8.000	71.000	.062
	Hotelling's Trace	.223	1.977[b]	8.000	71.000	.062
	Roy's Largest Root	.223	1.977[b]	8.000	71.000	.062
FDlevel * Gender	Pillai's Trace	.169	1.800[b]	8.000	71.000	.091
	Wilks' Lambda	.831	1.800[b]	8.000	71.000	.091
	Hotelling's Trace	.203	1.800[b]	8.000	71.000	.091
	Roy's Largest Root	.203	1.800[b]	8.000	71.000	.091

a. Design: Intercept + Gender
Within Subjects Design: FDlevel
b. Exact statistic

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FDlevel	.000	782.174	35	.000	.193	.198	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + Gender
Within Subjects Design: FDlevel

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Sphericity Assumed	221.176	8	27.647	2.267	.021
	Greenhouse-Geisser	221.176	1.542	143.451	2.267	.121
	Huynh-Feldt	221.176	1.587	139.360	2.267	.119
	Lower-bound	221.176	1.000	221.176	2.267	.136
FDlevel * Gender	Sphericity Assumed	346.026	8	43.253	3.547	.000
	Greenhouse-Geisser	346.026	1.542	224.427	3.547	.043
	Huynh-Feldt	346.026	1.587	218.026	3.547	.042
	Lower-bound	346.026	1.000	346.026	3.547	.063
Error(FDlevel)	Sphericity Assumed	7609.324	624	12.194		
	Greenhouse-Geisser	7609.324	120.262	63.273		
	Huynh-Feldt	7609.324	123.793	61.468		
	Lower-bound	7609.324	78.000	97.555		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	FDlevel	Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Linear	110.201	1	110.201	1.519	.221
	Quadratic	80.871	1	80.871	10.635	.002
	Cubic	3.321	1	3.321	1.005	.319
	Order 4	8.752	1	8.752	3.556	.063
	Order 5	5.488	1	5.488	2.482	.119
	Order 6	.376	1	.376	.152	.697
	Order 7	.019	1	.019	.004	.950
	Order 8	12.149	1	12.149	5.269	.024
FDlevel * Gender	Linear	327.695	1	327.695	4.518	.037
	Quadratic	.327	1	.327	.043	.836
	Cubic	13.533	1	13.533	4.096	.046
	Order 4	1.717	1	1.717	.697	.406

	Order 5	.698	1	.698	.316	.576
	Order 6	2.018	1	2.018	.818	.369
	Order 7	.002	1	.002	.000	.985
	Order 8	.036	1	.036	.016	.901
Error(FDlevel)	Linear	5657.558	78	72.533		
	Quadratic	593.122	78	7.604		
	Cubic	257.716	78	3.304		
	Order 4	191.983	78	2.461		
	Order 5	172.485	78	2.211		
	Order 6	192.507	78	2.468		
	Order 7	364.126	78	4.668		
	Order 8	179.828	78	2.305		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	23587.200	1	23587.200	.	.
Gender	.000	1	.000	.	.
Error	.000	78	.000		

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

FDlevel	Dependent Variable
1	FD11
2	FD12
3	FD13
4	FD14
5	FD15
6	FD16
7	FD17
8	FD18
9	FD19

Between-Subjects Factors

	Value Label	N

Enviro	1.0	urban	23
	2.0	rural	35
	3.0	suburban	20

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
FDlevel	Pillai's Trace	.185	1.930[b]	8.000	68.000	.069
	Wilks' Lambda	.815	1.930[b]	8.000	68.000	.069
	Hotelling's Trace	.227	1.930[b]	8.000	68.000	.069
	Roy's Largest Root	.227	1.930[b]	8.000	68.000	.069
FDlevel * Enviro	Pillai's Trace	.281	1.409	16.000	138.000	.146
	Wilks' Lambda	.738	1.395[b]	16.000	136.000	.153
	Hotelling's Trace	.330	1.381	16.000	134.000	.160
	Roy's Largest Root	.208	1.791[c]	8.000	69.000	.094

a. Design: Intercept + Enviro
Within Subjects Design: FDlevel
b. Exact statistic
c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b] Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FDlevel	.000	728.070	35	.000	.196	.205	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.
a. Design: Intercept + Enviro
Within Subjects Design: FDlevel
b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Sphericity Assumed	235.479	8	29.435	2.523	.011
	Greenhouse-Geisser	235.479	1.570	149.982	2.523	.097
	Huynh-Feldt	235.479	1.641	143.539	2.523	.095
	Lower-bound	235.479	1.000	235.479	2.523	.116
FDlevel * Enviro	Sphericity Assumed	740.410	16	46.276	3.967	.000
	Greenhouse-Geisser	740.410	3.140	235.792	3.967	.009
	Huynh-Feldt	740.410	3.281	225.662	3.967	.008
	Lower-bound	740.410	2.000	370.205	3.967	.023
Error(FDlevel)	Sphericity Assumed	6999.488	600	11.666		
	Greenhouse-Geisser	6999.488	117.754	59.442		
	Huynh-Feldt	6999.488	123.040	56.888		
	Lower-bound	6999.488	75.000	93.327		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	FDlevel	Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Linear	97.001	1	97.001	1.404	.240
	Quadratic	102.129	1	102.129	13.824	.000
	Cubic	.981	1	.981	.310	.579
	Order 4	12.587	1	12.587	5.080	.027
	Order 5	6.677	1	6.677	2.993	.088
	Order 6	4.833E-5	1	4.833E-5	.000	.996
	Order 7	2.399	1	2.399	.573	.451
	Order 8	13.704	1	13.704	5.809	.018
FDlevel * Enviro	Linear	634.576	2	317.288	4.593	.013
	Quadratic	32.443	2	16.221	2.196	.118
	Cubic	17.583	2	8.792	2.780	.068
	Order 4	6.694	2	3.347	1.351	.265
	Order 5	3.148	2	1.574	.705	.497
	Order 6	6.409	2	3.204	1.312	.275

	Order 7	39.304	2	19.652	4.692	.012
	Order 8	.254	2	.127	.054	.948
Error(FDlevel)	Linear	5180.807	75	69.077		
	Quadratic	554.064	75	7.388		
	Cubic	237.173	75	3.162		
	Order 4	185.844	75	2.478		
	Order 5	167.334	75	2.231		
	Order 6	183.202	75	2.443		
	Order 7	314.140	75	4.189		
	Order 8	176.923	75	2.359		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	23891.908	1	23891.908	.	.
Enviro	.000	2	.000	.	.
Error	.000	75	.000		

One-way ANOVA's

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
FD11	Between Groups	116.944	2	58.472	4.253	.018
	Within Groups	1031.171	75	13.749		
	Total	1148.115	77			
FD12	Between Groups	113.411	2	56.705	4.395	.016
	Within Groups	967.769	75	12.904		
	Total	1081.179	77			
FD13	Between Groups	120.101	2	60.051	4.867	.010
	Within Groups	925.348	75	12.338		
	Total	1045.449	77			
FD14	Between Groups	5.048	2	2.524	.619	.541
	Within Groups	305.824	75	4.078		
	Total	310.872	77			
FD15	Between Groups	19.186	2	9.593	3.715	.029
	Within Groups	193.686	75	2.582		
	Total	212.872	77			
FD16	Between Groups	6.803	2	3.401	.990	.377

	Within Groups	257.812	75	3.437		
	Total	264.615	77			
FD17	Between Groups	122.986	2	61.493	4.631	.013
	Within Groups	995.847	75	13.278		
	Total	1118.833	77			
FD18	Between Groups	82.156	2	41.078	2.778	.069
	Within Groups	1109.190	75	14.789		
	Total	1191.346	77			
FD19	Between Groups	153.774	2	76.887	4.755	.011
	Within Groups	1212.841	75	16.171		
	Total	1366.615	77			

Multiple Comparisons

Tukey HSD

Dependent Variable	(I) Enviro	(J) Enviro	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
FD11	urban	rural	2.8944*	.9953	.013	.515	5.274
		suburban	1.9587	1.1337	.202	-.752	4.669
	rural	urban	-2.8944*	.9953	.013	-5.274	-.515
		suburban	-.9357	1.0394	.642	-3.421	1.550
	suburban	urban	-1.9587	1.1337	.202	-4.669	.752
		rural	.9357	1.0394	.642	-1.550	3.421
FD12	urban	rural	2.8273*	.9642	.012	.522	5.133
		suburban	2.1130	1.0983	.139	-.513	4.739
	rural	urban	-2.8273*	.9642	.012	-5.133	-.522
		suburban	-.7143	1.0069	.759	-3.122	1.693
	suburban	urban	-2.1130	1.0983	.139	-4.739	.513
		rural	.7143	1.0069	.759	-1.693	3.122
FD13	urban	rural	2.9416*	.9428	.007	.687	5.196
		suburban	1.7630	1.0739	.235	-.805	4.331
	rural	urban	-2.9416*	.9428	.007	-5.196	-.687
		suburban	-1.1786	.9846	.459	-3.533	1.176
	suburban	urban	-1.7630	1.0739	.235	-4.331	.805
		rural	1.1786	.9846	.459	-1.176	3.533
FD14	urban	rural	.1938	.5420	.932	-1.102	1.490
		suburban	-.4348	.6174	.762	-1.911	1.041
	rural	urban	-.1938	.5420	.932	-1.490	1.102
		suburban	-.6286	.5660	.511	-1.982	.725

	suburban	urban	.4348	.6174	.762	-1.041	1.911
		rural	.6286	.5660	.511	-.725	1.982
FD15	urban	rural	.0571	.4314	.990	-.974	1.089
		suburban	-1.1000	.4913	.071	-2.275	.075
	rural	urban	-.0571	.4314	.990	-1.089	.974
		suburban	-1.1571*	.4505	.032	-2.234	-.080
	suburban	urban	1.1000	.4913	.071	-.075	2.275
		rural	1.1571*	.4505	.032	.080	2.234
FD16	urban	rural	-.4099	.4977	.690	-1.600	.780
		suburban	-.7957	.5669	.344	-2.151	.560
	rural	urban	.4099	.4977	.690	-.780	1.600
		suburban	-.3857	.5197	.739	-1.628	.857
	suburban	urban	.7957	.5669	.344	-.560	2.151
		rural	.3857	.5197	.739	-.857	1.628
FD17	urban	rural	-2.9404*	.9781	.010	-5.279	-.602
		suburban	-1.3261	1.1141	.463	-3.990	1.338
	rural	urban	2.9404*	.9781	.010	.602	5.279
		suburban	1.6143	1.0214	.260	-.828	4.057
	suburban	urban	1.3261	1.1141	.463	-1.338	3.990
		rural	-1.6143	1.0214	.260	-4.057	.828
FD18	urban	rural	-2.4311	1.0323	.054	-4.899	.037
		suburban	-1.3739	1.1758	.476	-4.185	1.438
	rural	urban	2.4311	1.0323	.054	-.037	4.899
		suburban	1.0571	1.0780	.591	-1.520	3.635
	suburban	urban	1.3739	1.1758	.476	-1.438	4.185
		rural	-1.0571	1.0780	.591	-3.635	1.520
FD19	urban	rural	-3.1329*	1.0794	.013	-5.714	-.552
		suburban	-.8043	1.2295	.791	-3.744	2.136
	rural	urban	3.1329*	1.0794	.013	.552	5.714
		suburban	2.3286	1.1272	.104	-.367	5.024
	suburban	urban	.8043	1.2295	.791	-2.136	3.744
		rural	-2.3286	1.1272	.104	-5.024	.367

*. The mean difference is significant at the 0.05 level.

Chapter 11 Output:

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

FDlevel	Dependent Variable
1	FD11
2	FD12
3	FD13
4	FD14
5	FD15
6	FD16
7	FD17
8	FD18
9	FD19

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
FDlevel	Pillai's Trace	.528	5.877[b]	8.000	42.000	.000
	Wilks' Lambda	.472	5.877[b]	8.000	42.000	.000
	Hotelling's Trace	1.119	5.877[b]	8.000	42.000	.000
	Roy's Largest Root	1.119	5.877[b]	8.000	42.000	.000

a. Design: Intercept
Within Subjects Design: FDlevel
b. Exact statistic

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FDlevel	.000	455.639	35	.000	.187	.192	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.
a. Design: Intercept
Within Subjects Design: FDlevel
b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Sphericity Assumed	2211.200	8	276.400	31.074	.000
	Greenhouse-Geisser	2211.200	1.498	1475.705	31.074	.000
	Huynh-Feldt	2211.200	1.535	1440.419	31.074	.000
	Lower-bound	2211.200	1.000	2211.200	31.074	.000
Error(FDlevel)	Sphericity Assumed	3486.800	392	8.895		
	Greenhouse-Geisser	3486.800	73.422	47.490		
	Huynh-Feldt	3486.800	75.220	46.354		
	Lower-bound	3486.800	49.000	71.159		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	FDlevel	Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Linear	1981.281	1	1981.281	36.096	.000
	Quadratic	10.286	1	10.286	3.463	.069
	Cubic	89.261	1	89.261	25.696	.000
	Order 4	1.114	1	1.114	.642	.427
	Order 5	22.401	1	22.401	13.842	.001
	Order 6	3.078	1	3.078	2.099	.154
	Order 7	97.197	1	97.197	30.767	.000
	Order 8	6.582	1	6.582	3.564	.065
Error(FDlevel)	Linear	2689.552	49	54.889		
	Quadratic	145.552	49	2.970		
	Cubic	170.214	49	3.474		
	Order 4	85.051	49	1.736		
	Order 5	79.296	49	1.618		
	Order 6	71.859	49	1.467		
	Order 7	154.798	49	3.159		
	Order 8	90.478	49	1.846		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	16200.000	1	16200.000	13964677282057420000.000	.000
Error	5.684E-14	49	1.160E-15		

Estimated Marginal Means
FDlevel

Estimates

Measure: MEASURE_1

FDlevel	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1	8.360	.509	7.337	9.383
2	8.780	.473	7.829	9.731
3	8.540	.434	7.669	9.411
4	6.600	.204	6.190	7.010
5	6.120	.184	5.749	6.491
6	6.100	.241	5.615	6.585
7	3.100	.436	2.223	3.977
8	3.200	.458	2.280	4.120
9	3.200	.467	2.262	4.138

Pairwise Comparisons

Measure: MEASURE_1

(I) FDlevel	(J) FDlevel	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	-.420	.276	1.000	-1.354	.514
	3	-.180	.275	1.000	-1.112	.752
	4	1.760	.521	.052	-.006	3.526
	5	2.240*	.586	.013	.254	4.226
	6	2.260*	.657	.043	.033	4.487
	7	5.260*	.899	.000	2.211	8.309
	8	5.160*	.923	.000	2.030	8.290
	9	5.160*	.948	.000	1.947	8.373
2	1	.420	.276	1.000	-.514	1.354
	3	.240	.207	1.000	-.462	.942
	4	2.180*	.475	.001	.569	3.791
	5	2.660*	.533	.000	.852	4.468

	6	2.680*	.626	.003	.557	4.803
	7	5.680*	.883	.000	2.686	8.674
	8	5.580*	.899	.000	2.531	8.629
	9	5.580*	.910	.000	2.496	8.664
3	1	.180	.275	1.000	-.752	1.112
	2	-.240	.207	1.000	-.942	.462
	4	1.940*	.431	.001	.479	3.401
	5	2.420*	.489	.000	.762	4.078
	6	2.440*	.575	.004	.490	4.390
	7	5.440*	.843	.000	2.581	8.299
	8	5.340*	.870	.000	2.390	8.290
	9	5.340*	.879	.000	2.362	8.318
4	1	-1.760	.521	.052	-3.526	.006
	2	-2.180*	.475	.001	-3.791	-.569
	3	-1.940*	.431	.001	-3.401	-.479
	5	.480	.241	1.000	-.337	1.297
	6	.500	.327	1.000	-.610	1.610
	7	3.500*	.539	.000	1.672	5.328
	8	3.400*	.569	.000	1.470	5.330
	9	3.400*	.579	.000	1.439	5.361
5	1	-2.240*	.586	.013	-4.226	-.254
	2	-2.660*	.533	.000	-4.468	-.852
	3	-2.420*	.489	.000	-4.078	-.762
	4	-.480	.241	1.000	-1.297	.337
	6	.020	.308	1.000	-1.025	1.065
	7	3.020*	.469	.000	1.430	4.610
	8	2.920*	.498	.000	1.232	4.608
	9	2.920*	.491	.000	1.257	4.583
6	1	-2.260*	.657	.043	-4.487	-.033
	2	-2.680*	.626	.003	-4.803	-.557
	3	-2.440*	.575	.004	-4.390	-.490
	4	-.500	.327	1.000	-1.610	.610
	5	-.020	.308	1.000	-1.065	1.025
	7	3.000*	.442	.000	1.503	4.497
	8	2.900*	.448	.000	1.380	4.420
	9	2.900*	.440	.000	1.408	4.392
7	1	-5.260*	.899	.000	-8.309	-2.211
	2	-5.680*	.883	.000	-8.674	-2.686
	3	-5.440*	.843	.000	-8.299	-2.581
	4	-3.500*	.539	.000	-5.328	-1.672
	5	-3.020*	.469	.000	-4.610	-1.430

	6	-3.000*	.442	.000	-4.497	-1.503
	8	-.100	.258	1.000	-.973	.773
	9	-.100	.254	1.000	-.962	.762
8	1	-5.160*	.923	.000	-8.290	-2.030
	2	-5.580*	.899	.000	-8.629	-2.531
	3	-5.340*	.870	.000	-8.290	-2.390
	4	-3.400*	.569	.000	-5.330	-1.470
	5	-2.920*	.498	.000	-4.608	-1.232
	6	-2.900*	.448	.000	-4.420	-1.380
	7	.100	.258	1.000	-.773	.973
	9	.000	.230	1.000	-.781	.781
9	1	-5.160*	.948	.000	-8.373	-1.947
	2	-5.580*	.910	.000	-8.664	-2.496
	3	-5.340*	.879	.000	-8.318	-2.362
	4	-3.400*	.579	.000	-5.361	-1.439
	5	-2.920*	.491	.000	-4.583	-1.257
	6	-2.900*	.440	.000	-4.392	-1.408
	7	.100	.254	1.000	-.762	.962
	8	.000	.230	1.000	-.781	.781

Based on estimated marginal means

*. The mean difference is significant at the

b. Adjustment for multiple comparisons: Bonferroni.

Multivariate Tests

	Value	F	Hypothesis df	Error df	Sig.
Pillai's trace	.528	5.877[a]	8.000	42.000	.000
Wilks' lambda	.472	5.877[a]	8.000	42.000	.000
Hotelling's trace	1.119	5.877[a]	8.000	42.000	.000
Roy's largest root	1.119	5.877[a]	8.000	42.000	.000

Each F tests the multivariate effect of FDlevel. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

FDlevel	Dependent Variable
1	FD11
2	FD12
3	FD13

4	FD14
5	FD15
6	FD16
7	FD17
8	FD18
9	FD19

Between-Subjects Factors

		Value Label	N
enviro	1	urban	31
	2	rural	19

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
FDlevel	Pillai's Trace	.536	5.913[b]	8.000	41.000	.000
	Wilks' Lambda	.464	5.913[b]	8.000	41.000	.000
	Hotelling's Trace	1.154	5.913[b]	8.000	41.000	.000
	Roy's Largest Root	1.154	5.913[b]	8.000	41.000	.000
FDlevel * enviro	Pillai's Trace	.166	1.021[b]	8.000	41.000	.436
	Wilks' Lambda	.834	1.021[b]	8.000	41.000	.436
	Hotelling's Trace	.199	1.021[b]	8.000	41.000	.436
	Roy's Largest Root	.199	1.021[b]	8.000	41.000	.436

a. Design: Intercept + enviro

Within Subjects Design: FDlevel

b. Exact statistic

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b] Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FDlevel	.000	450.720	35	.000	.186	.195	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + enviro
Within Subjects Design: FDlevel
b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Sphericity Assumed	2172.590	8	271.574	30.178	.000
	Greenhouse-Geisser	2172.590	1.488	1460.536	30.178	.000
	Huynh-Feldt	2172.590	1.556	1396.207	30.178	.000
	Lower-bound	2172.590	1.000	2172.590	30.178	.000
FDlevel * enviro	Sphericity Assumed	31.150	8	3.894	.433	.901
	Greenhouse-Geisser	31.150	1.488	20.941	.433	.591
	Huynh-Feldt	31.150	1.556	20.018	.433	.600
	Lower-bound	31.150	1.000	31.150	.433	.514
Error(FDlevel)	Sphericity Assumed	3455.650	384	8.999		
	Greenhouse-Geisser	3455.650	71.401	48.398		
	Huynh-Feldt	3455.650	74.691	46.266		
	Lower-bound	3455.650	48.000	71.993		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	FDlevel	Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Linear	1933.713	1	1933.713	34.641	.000
	Quadratic	7.672	1	7.672	2.566	.116
	Cubic	86.800	1	86.800	24.530	.000
	Order 4	.888	1	.888	.502	.482
	Order 5	21.765	1	21.765	13.190	.001
	Order 6	2.918	1	2.918	1.949	.169
	Order 7	110.188	1	110.188	37.806	.000

	Order 8	8.646	1	8.646	4.772	.034
FDlevel * enviro	Linear	10.117	1	10.117	.181	.672
	Quadratic	2.050	1	2.050	.686	.412
	Cubic	.365	1	.365	.103	.749
	Order 4	.119	1	.119	.067	.797
	Order 5	.087	1	.087	.053	.820
	Order 6	.000	1	.000	.000	.986
	Order 7	14.898	1	14.898	5.111	.028
	Order 8	3.515	1	3.515	1.940	.170
Error(FDlevel)	Linear	2679.435	48	55.822		
	Quadratic	143.502	48	2.990		
	Cubic	169.849	48	3.539		
	Order 4	84.933	48	1.769		
	Order 5	79.209	48	1.650		
	Order 6	71.858	48	1.497		
	Order 7	139.900	48	2.915		
	Order 8	86.964	48	1.812		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	15266.880	1	15266.880	3222933519333 284900.000	.000
enviro	.000	1	.000	.000	1.000
Error	2.274E-13	48	4.737E-15		

T-Test

Group Statistics

	enviro	N	Mean	Std. Deviation	Std. Error Mean
CNS	urban	31	48.1613	7.07152	1.27008
	rural	19	48.5789	8.95864	2.05525

Independent Samples Test

	Levene's Test for Equality of Variances	t-test for Equality of Means

		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	Upper
CNS	Equal variances assumed	1.690	.200	-.183	48	.856	-.41766	2.28211	-5.00615	4.17083
	Equal variances not assumed			-.173	31.607	.864	-.41766	2.41603	-5.34134	4.50603

T-Test

Group Statistics

	Gender	N	Mean	Std. Deviation	Std. Error Mean
CNS	Male	16	51.8750	6.21691	1.55423
	Female	34	46.6471	7.91960	1.35820

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
CNS	Equal variances assumed	.656	.422	2.321	48	.025	5.22794	2.25241	.69916	9.75672
	Equal variances not assumed			2.533	36.881	.016	5.22794	2.06406	1.04531	9.41058

Chapter 12 Output:

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

FDlevel	Dependent Variable
1	D1.1
2	D1.2
3	D1.3
4	D1.4
5	D1.5
6	D1.6
7	D1.7
8	D1.8
9	D1.9

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
FDlevel	Pillai's Trace	.198	16.190[b]	8.000	523.000	.000
	Wilks' Lambda	.802	16.190[b]	8.000	523.000	.000
	Hotelling's Trace	.248	16.190[b]	8.000	523.000	.000
	Roy's Largest Root	.248	16.190[b]	8.000	523.000	.000

a. Design: Intercept
Within Subjects Design: FDlevel
b. Exact statistic

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FDlevel	.000	5518.759	35	.000	.183	.184	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.
a. Design: Intercept
Within Subjects Design: FDlevel
b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Sphericity Assumed	3434.228	8	429.278	35.061	.000
	Greenhouse-Geisser	3434.228	1.467	2341.144	35.061	.000
	Huynh-Feldt	3434.228	1.470	2336.266	35.061	.000
	Lower-bound	3434.228	1.000	3434.228	35.061	.000
Error(FDlevel)	Sphericity Assumed	51914.217	4240	12.244		
	Greenhouse-Geisser	51914.217	777.458	66.774		
	Huynh-Feldt	51914.217	779.081	66.635		
	Lower-bound	51914.217	530.000	97.951		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	FDlevel	Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Linear	2725.793	1	2725.793	35.999	.000
	Quadratic	380.474	1	380.474	66.966	.000
	Cubic	143.189	1	143.189	38.935	.000
	Order 4	47.313	1	47.313	19.971	.000
	Order 5	50.856	1	50.856	23.733	.000
	Order 6	3.869	1	3.869	1.891	.170
	Order 7	37.366	1	37.366	8.740	.003
	Order 8	45.368	1	45.368	22.236	.000
Error(FDlevel)	Linear	40131.057	530	75.719		
	Quadratic	3011.231	530	5.682		
	Cubic	1949.140	530	3.678		
	Order 4	1255.591	530	2.369		
	Order 5	1135.706	530	2.143		
	Order 6	1084.245	530	2.046		
	Order 7	2265.893	530	4.275		
	Order 8	1081.353	530	2.040		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	171600.286	1	171600.286	1007522.595	.000
Error	90.269	530	.170		

Estimated Marginal Means
FDlevel

Estimates

Measure: MEASURE_1

FDlevel	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1	6.516	.170	6.182	6.850
2	6.889	.169	6.557	7.221
3	6.802	.159	6.489	7.115
4	6.653	.078	6.501	6.806
5	6.292	.072	6.151	6.433
6	6.282	.078	6.130	6.435
7	5.064	.158	4.753	5.375
8	4.697	.169	4.364	5.029
9	4.734	.176	4.389	5.080

Pairwise Comparisons

Measure: MEASURE_1

(I) FDlevel	(J) FDlevel	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	-.373*	.075	.000	-.615	-.130
	3	-.286*	.078	.009	-.536	-.037
	4	-.137	.173	1.000	-.695	.420
	5	.224	.192	1.000	-.393	.841
	6	.234	.215	1.000	-.458	.925
	7	1.452*	.318	.000	.431	2.473
	8	1.819*	.328	.000	.764	2.874
	9	1.782*	.332	.000	.714	2.849
2	1	.373*	.075	.000	.130	.615

	3	.087	.081	1.000	-.174	.347
	4	.235	.170	1.000	-.312	.783
	5	.597	.189	.062	-.012	1.206
	6	.606	.212	.160	-.076	1.289
	7	1.825*	.318	.000	.803	2.847
	8	2.192*	.328	.000	1.136	3.248
	9	2.154*	.332	.000	1.087	3.222
3	1	.286*	.078	.009	.037	.536
	2	-.087	.081	1.000	-.347	.174
	4	.149	.161	1.000	-.370	.668
	5	.510	.179	.159	-.063	1.084
	6	.520	.200	.346	-.123	1.163
	7	1.738*	.308	.000	.749	2.727
	8	2.105*	.319	.000	1.080	3.131
	9	2.068*	.324	.000	1.025	3.110
4	1	.137	.173	1.000	-.420	.695
	2	-.235	.170	1.000	-.783	.312
	3	-.149	.161	1.000	-.668	.370
	5	.362*	.090	.002	.074	.649
	6	.371*	.102	.011	.044	.698
	7	1.589*	.199	.000	.951	2.228
	8	1.957*	.213	.000	1.273	2.640
	9	1.919*	.224	.000	1.201	2.637
5	1	-.224	.192	1.000	-.841	.393
	2	-.597	.189	.062	-1.206	.012
	3	-.510	.179	.159	-1.084	.063
	4	-.362*	.090	.002	-.649	-.074
	6	.009	.088	1.000	-.273	.292
	7	1.228*	.180	.000	.649	1.807
	8	1.595*	.192	.000	.978	2.212
	9	1.557*	.201	.000	.911	2.204
6	1	-.234	.215	1.000	-.925	.458
	2	-.606	.212	.160	-1.289	.076
	3	-.520	.200	.346	-1.163	.123
	4	-.371*	.102	.011	-.698	-.044
	5	-.009	.088	1.000	-.292	.273
	7	1.218*	.161	.000	.702	1.734
	8	1.586*	.173	.000	1.030	2.142
	9	1.548*	.183	.000	.959	2.137
7	1	-1.452*	.318	.000	-2.473	-.431
	2	-1.825*	.318	.000	-2.847	-.803

	3	-1.738*	.308	.000	-2.727	-.749
	4	-1.589*	.199	.000	-2.228	-.951
	5	-1.228*	.180	.000	-1.807	-.649
	6	-1.218*	.161	.000	-1.734	-.702
	8	.367*	.086	.001	.092	.643
	9	.330*	.091	.011	.038	.621
8	1	-1.819*	.328	.000	-2.874	-.764
	2	-2.192*	.328	.000	-3.248	-1.136
	3	-2.105*	.319	.000	-3.131	-1.080
	4	-1.957*	.213	.000	-2.640	-1.273
	5	-1.595*	.192	.000	-2.212	-.978
	6	-1.586*	.173	.000	-2.142	-1.030
	7	-.367*	.086	.001	-.643	-.092
	9	-.038	.074	1.000	-.276	.200
9	1	-1.782*	.332	.000	-2.849	-.714
	2	-2.154*	.332	.000	-3.222	-1.087
	3	-2.068*	.324	.000	-3.110	-1.025
	4	-1.919*	.224	.000	-2.637	-1.201
	5	-1.557*	.201	.000	-2.204	-.911
	6	-1.548*	.183	.000	-2.137	-.959
	7	-.330*	.091	.011	-.621	-.038
	8	.038	.074	1.000	-.200	.276

Based on estimated marginal means

*. The mean difference is significant at the

b. Adjustment for multiple comparisons: Bonferroni.

Multivariate Tests

	Value	F	Hypothesis df	Error df	Sig.
Pillai's trace	.198	16.190[a]	8.000	523.000	.000
Wilks' lambda	.802	16.190[a]	8.000	523.000	.000
Hotelling's trace	.248	16.190[a]	8.000	523.000	.000
Roy's largest root	.248	16.190[a]	8.000	523.000	.000

Each F tests the multivariate effect of FDlevel. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

FDlevel	Dependent Variable
1	D1.1
2	D1.2
3	D1.3
4	D1.4
5	D1.5
6	D1.6
7	D1.7
8	D1.8
9	D1.9

Between-Subjects Factors

		Value Label	N
NewLocationGroup	1.00	Europe	177
	2.00	North America	24
	3.00	Central Asia	195
	5.00	Africa	97

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
FDlevel	Pillai's Trace	.117	8.019[b]	8.000	482.000	.000
	Wilks' Lambda	.883	8.019[b]	8.000	482.000	.000
	Hotelling's Trace	.133	8.019[b]	8.000	482.000	.000
	Roy's Largest Root	.133	8.019[b]	8.000	482.000	.000
FDlevel * NewLocationGroup	Pillai's Trace	.091	1.903	24.000	1452.000	.005
	Wilks' Lambda	.911	1.899	24.000	1398.548	.006
	Hotelling's Trace	.095	1.894	24.000	1442.000	.006
	Roy's Largest Root	.042	2.557[c]	8.000	484.000	.010

a. Design: Intercept + NewLocationGroup
 Within Subjects Design: FDlevel

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FDlevel	.000	4995.552	35	.000	.184	.186	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + NewLocationGroup
Within Subjects Design: FDlevel

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Sphericity Assumed	820.175	8	102.522	8.625	.000
	Greenhouse-Geisser	820.175	1.474	556.572	8.625	.001
	Huynh-Feldt	820.175	1.486	551.912	8.625	.001
	Lower-bound	820.175	1.000	820.175	8.625	.003
FDlevel * NewLocationGroup	Sphericity Assumed	1139.739	24	47.489	3.995	.000
	Greenhouse-Geisser	1139.739	4.421	257.810	3.995	.002
	Huynh-Feldt	1139.739	4.458	255.651	3.995	.002
	Lower-bound	1139.739	3.000	379.913	3.995	.008
Error(FDlevel)	Sphericity Assumed	46500.891	3912	11.887		
	Greenhouse-Geisser	46500.891	720.600	64.531		
	Huynh-Feldt	46500.891	726.684	63.991		
	Lower-bound	46500.891	489.000	95.094		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	FDlevel	Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Linear	527.670	1	527.670	7.187	.008
	Quadratic	165.561	1	165.561	31.183	.000
	Cubic	61.464	1	61.464	16.860	.000
	Order 4	15.131	1	15.131	6.327	.012
	Order 5	13.408	1	13.408	6.388	.012
	Order 6	2.247	1	2.247	1.099	.295
	Order 7	.644	1	.644	.155	.694
	Order 8	34.049	1	34.049	16.736	.000
FDlevel * NewLocationGroup	Linear	997.070	3	332.357	4.527	.004
	Quadratic	28.372	3	9.457	1.781	.150
	Cubic	26.927	3	8.976	2.462	.062
	Order 4	6.281	3	2.094	.875	.454
	Order 5	17.546	3	5.849	2.787	.040
	Order 6	6.051	3	2.017	.987	.399
	Order 7	45.998	3	15.333	3.697	.012
	Order 8	11.494	3	3.831	1.883	.131
Error(FDlevel)	Linear	35903.654	489	73.423		
	Quadratic	2596.249	489	5.309		
	Cubic	1782.659	489	3.646		
	Order 4	1169.403	489	2.391		
	Order 5	1026.331	489	2.099		
	Order 6	999.808	489	2.045		
	Order 7	2027.958	489	4.147		
	Order 8	994.828	489	2.034		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	82323.552	1	82323.552	512700.510	.000
NewLocationGroup	1.026	3	.342	2.130	.096
Error	78.518	489	.161		

Estimated Marginal Means

1. FDlevel

2. NewLocationGroup

Estimates

Measure: MEASURE_1

NewLocationGroup	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Europe	5.965	.010	5.945	5.985
North America	6.000	.027	5.946	6.054
Central Asia	5.994	.010	5.975	6.013
Africa	6.000	.014	5.973	6.027

Pairwise Comparisons

Measure: MEASURE_1

(I) NewLocationGroup	(J) NewLocationGroup	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
Europe	North America	-.035	.029	1.000	-.112	.042
	Central Asia	-.029	.014	.227	-.066	.008
	Africa	-.035	.017	.226	-.080	.010
North America	Europe	.035	.029	1.000	-.042	.112
	Central Asia	.006	.029	1.000	-.070	.083
	Africa	3.886E-16	.030	1.000	-.081	.081
Central Asia	Europe	.029	.014	.227	-.008	.066
	North America	-.006	.029	1.000	-.083	.070
	Africa	-.006	.017	1.000	-.050	.038
Africa	Europe	.035	.017	.226	-.010	.080
	North America	-3.886E-16	.030	1.000	-.081	.081
	Central Asia	.006	.017	1.000	-.038	.050

Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Measure: MEASURE_1

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	.114	3	.038	2.130	.096
Error	8.724	489	.018		

The F tests the effect of NewLocationGroup. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

FDlevel	Dependent Variable
1	D1.1
2	D1.2
3	D1.3
4	D1.4
5	D1.5
6	D1.6
7	D1.7
8	D1.8
9	D1.9

Between-Subjects Factors

		Value Label	N
Gender	1	Male	257
	2	Female	273

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
FDlevel	Pillai's Trace	.198	16.036[b]	8.000	521.000	.000
	Wilks' Lambda	.802	16.036[b]	8.000	521.000	.000
	Hotelling's Trace	.246	16.036[b]	8.000	521.000	.000
	Roy's Largest Root	.246	16.036[b]	8.000	521.000	.000
FDlevel * Gender	Pillai's Trace	.047	3.221[b]	8.000	521.000	.001
	Wilks' Lambda	.953	3.221[b]	8.000	521.000	.001
	Hotelling's Trace	.049	3.221[b]	8.000	521.000	.001
	Roy's Largest Root	.049	3.221[b]	8.000	521.000	.001

a. Design: Intercept + Gender
Within Subjects Design: FDlevel

b. Exact statistic

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
FDlevel	.000	5483.484	35	.000	.184	.184	.125

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + Gender
 Within Subjects Design: FDlevel

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Sphericity Assumed	3460.690	8	432.586	35.563	.000
	Greenhouse-Geisser	3460.690	1.469	2355.864	35.563	.000
	Huynh-Feldt	3460.690	1.475	2346.472	35.563	.000
	Lower-bound	3460.690	1.000	3460.690	35.563	.000
FDlevel * Gender	Sphericity Assumed	495.543	8	61.943	5.092	.000
	Greenhouse-Geisser	495.543	1.469	337.341	5.092	.013
	Huynh-Feldt	495.543	1.475	335.996	5.092	.013
	Lower-bound	495.543	1.000	495.543	5.092	.024
Error(FDlevel)	Sphericity Assumed	51381.114	4224	12.164		
	Greenhouse-Geisser	51381.114	775.615	66.246		
	Huynh-Feldt	51381.114	778.720	65.982		
	Lower-bound	51381.114	528.000	97.313		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	FDlevel	Type III Sum of Squares	df	Mean Square	F	Sig.
FDlevel	Linear	2764.224	1	2764.224	36.815	.000
	Quadratic	372.175	1	372.175	65.532	.000
	Cubic	144.379	1	144.379	39.376	.000
	Order 4	46.153	1	46.153	19.471	.000
	Order 5	50.366	1	50.366	23.425	.000
	Order 6	3.368	1	3.368	1.649	.200
	Order 7	36.030	1	36.030	8.412	.004
	Order 8	43.996	1	43.996	21.601	.000
FDlevel * Gender	Linear	463.074	1	463.074	6.167	.013
	Quadratic	5.255	1	5.255	.925	.337
	Cubic	12.303	1	12.303	3.355	.068
	Order 4	3.956	1	3.956	1.669	.197
	Order 5	.431	1	.431	.201	.654
	Order 6	1.607	1	1.607	.787	.375
	Order 7	3.194	1	3.194	.746	.388
	Order 8	5.723	1	5.723	2.810	.094
Error(FDlevel)	Linear	39644.563	528	75.084		
	Quadratic	2998.644	528	5.679		
	Cubic	1936.006	528	3.667		
	Order 4	1251.513	528	2.370		
	Order 5	1135.264	528	2.150		
	Order 6	1078.243	528	2.042		
	Order 7	2261.486	528	4.283		
	Order 8	1075.396	528	2.037		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	171247.255	1	171247.255	1141560.141	.000
Gender	.085	1	.085	.570	.451
Error	79.206	528	.150		

Estimated Marginal Means
Gender

Estimates

Measure: MEASURE_1

Gender	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Male	5.999	.008	5.983	6.015
Female	5.990	.008	5.975	6.006

Pairwise Comparisons

Measure: MEASURE_1

(I) Gender	(J) Gender	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
Male	Female	.008	.011	.451	-.014	.031
Female	Male	-.008	.011	.451	-.031	.014

Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Measure: MEASURE_1

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	.009	1	.009	.570	.451
Error	8.801	528	.017		

The F tests the effect of Gender. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

R Output

Chapter 9

```
>

> #Full Model

> print(m3a.ML <- glmer (complex ~ (cont2+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

 Data: df2[df2$study == "mturk", ]

 AIC  BIC logLik deviance

 6739 6830  -3358     6715

Random effects:

 Groups  Name        Variance Std.Dev.

 ID      (Intercept) 1.6795   1.2960

 display (Intercept) 4.3242   2.0795

Number of obs: 14361, groups: ID, 265; display, 41

Fixed effects:
```

Estimate Std. Error z value Pr(>|z|)

(Intercept) -4.497276 0.525598 -8.556 <2e-16 ***

cont2.c-e 0.389218 0.439757 0.885 0.3761

cont2.n-e 1.286396 0.579286 2.221 0.0264 *

gender.M-F 0.062031 0.515721 0.120 0.9043

cAge -0.004953 0.032326 -0.153 0.8782

cont2.c-e:gender.M-F 0.052843 0.556880 0.095 0.9244

cont2.n-e:gender.M-F -0.514157 0.769074 -0.669 0.5038

cont2.c-e:cAge 0.018819 0.031233 0.603 0.5468

cont2.n-e:cAge 0.010540 0.035142 0.300 0.7642

gender.M-F:cAge -0.012987 0.020046 -0.648 0.5171

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> #Null Model

> print(m3a0.ML <- glmer (complex ~ (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (1 | ID) + (1 | display)

Data: df2[df2$study == "mturk",]

AIC BIC logLik deviance

7023 7046 -3509 7017

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 1.7708 1.3307

display (Intercept) 4.5168 2.1253

Number of obs: 15009, groups: ID, 277; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -4.0584 0.3512 -11.56 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> #Check if full model is better than null model at accounting for variance.

> anova(m3a.ML,m3a0.ML)

Data: [

Data: df2

Data: df2$study == "mturk"

Data:

Models:

m3a0.ML: complex ~ (1 | ID) + (1 | display)

m3a.ML: complex ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m3a0.ML 3 7023.2 7046.1 -3508.6

m3a.ML 12 6739.1 6830.0 -3357.6 302.1 9 < 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> #Checking individual variables

> print(m3a1.ML <- glmer (complex ~ (gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2[df2$study == "mturk",]

AIC BIC logLik deviance

7028 7073 -3508 7016

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 1.7594 1.3264

display (Intercept) 4.5135 2.1245

Number of obs: 15009, groups: ID, 277; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -4.05476 0.36888 -10.992 <2e-16 ***

gender.M-F   -0.02250   0.18108 -0.124
0.901

cAge   0.01718   0.01428   1.203   0.229

gender.M-F:cAge -0.01695   0.01874 -0.904
0.366

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05
'.' 0.1 ' ' 1

>

> #Check if continent is a sig predictor

> anova(m3a.ML,m3a1.ML)

Data: [

Data: df2

Data: df2$study == "mturk"

Data:

Models:

m3a1.ML: complex ~ (gender + cAge)^2 + (1 |
ID) + (1 | display)

m3a.ML: complex ~ (cont2 + gender + cAge)^2
+ (1 | ID) + (1 | display)

       Df   AIC   BIC logLik Chisq Chi Df
Pr(>Chisq)

m3a1.ML 6 7027.7 7073.4 -3507.9

m3a.ML 12 6739.1 6830.0 -3357.6 300.57   6
< 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05
'.' 0.1 ' ' 1

> #Checking individual variables

> print(m3a2.ML <- glmer (complex ~
(cont2+cAge)^2 + (1 | ID) + (1| display),
family=binomial,
data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the
Laplace approximation

Formula: complex ~ (cont2 + cAge)^2 + (1 |
ID) + (1 | display)

   Data: df2[df2$study == "mturk",]

  AIC BIC logLik deviance

 6733 6793 -3358   6717

Random effects:

 Groups Name   Variance Std.Dev.

 ID   (Intercept) 1.6947   1.3018

 display (Intercept) 4.3258   2.0799

Number of obs: 14361, groups: ID, 265;
display, 41

Fixed effects:

            Estimate Std. Error z value Pr(>|z|)

(Intercept)   -4.46570   0.41766 -10.692 < 2e-
16 ***

cont2.c-e   0.43897   0.27032   1.624
0.10440

cont2.n-e   1.03104   0.39850   2.587
0.00967 **

cAge   -0.01432   0.02864 -0.500
0.61710

cont2.c-e:cAge 0.01916   0.03106   0.617
0.53718

cont2.n-e:cAge 0.01346   0.03463   0.389
0.69750

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05
'.' 0.1 ' ' 1

> #Check if continent is a sig predictor

> anova(m3a.ML,m3a2.ML)

Data: [

Data: df2

Data: df2$study == "mturk"

Data:

Models:

m3a2.ML: complex ~ (cont2 + cAge)^2 + (1 |
ID) + (1 | display)

m3a.ML: complex ~ (cont2 + gender + cAge)^2
+ (1 | ID) + (1 | display)

       Df   AIC   BIC logLik Chisq Chi Df
Pr(>Chisq)

m3a2.ML 8 6732.9 6793.4 -3358.4

m3a.ML 12 6739.1 6830.0 -3357.6 1.7214   4
0.7868

> #Checking individual variables

> print(m3a3.ML <- glmer (complex ~
(cont2+gender)^2 + (1 | ID) + (1| display),
family=binomial,
data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the
Laplace approximation

Formula: complex ~ (cont2 + gender)^2 + (1 |
ID) + (1 | display)

Data: df2[df2$study == "mturk",]

AIC BIC logLik deviance

6732 6793 -3358 6716

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 1.6856 1.2983

display (Intercept) 4.3264 2.0800

Number of obs: 14361, groups: ID, 265; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -4.49096 0.52396 -8.571 <2e-16 ***

cont2.c-e 0.40187 0.43624 0.921 0.3569

cont2.n-e 1.31897 0.55572 2.373 0.0176 *

gender.M-F 0.05480 0.51428 0.107 0.9151

cont2.c-e:gender.M-F 0.03892 0.55422 0.070 0.9440

cont2.n-e:gender.M-F -0.60514 0.74912 -0.808 0.4192

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> #Check if continent is a sig predictor

> anova(m3a.ML,m3a3.ML)

Data: [

Data: df2

Data: df2$study == "mturk"

Data:

Models:

m3a3.ML: complex ~ (cont2 + gender)^2 + (1 | ID) + (1 | display)

m3a.ML: complex ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m3a3.ML 8 6732.0 6792.6 -3358.0

m3a.ML 12 6739.1 6830.0 -3357.6 0.9057 4 0.9237

>

> ####### Mid-Range Model

>

> print(m3b.ML <- glmer (biCat2 ~ (cont2+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2[df2$study == "mturk",]

AIC BIC logLik deviance

11585 11676 -5780 11561

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.33868 0.58196

display (Intercept) 15.80376 3.97539

Number of obs: 14361, groups: ID, 265; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.8744063 0.6629297 2.828 0.00469 **

cont2.c-e 0.1183764 0.2097611 0.564 0.57252

cont2.n-e 0.7408349 0.2839014 2.610 0.00907 **

gender.M-F 0.1602208 0.2452925 0.653 0.51364

cAge 0.0009177 0.0154061 0.060 0.95250

cont2.c-e:gender.M-F -0.0513507 0.2656620 -0.193 0.84673

cont2.n-e:gender.M-F -0.7459233 0.3768743 -1.979 0.04779 *

cont2.c-e:cAge 0.0130469 0.0148550 0.878 0.37979

cont2.n-e:cAge 0.0164873 0.0168315 0.980 0.32731

gender.M-F:cAge -0.0081508 0.0098470 -0.828 0.40781

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>

```
> print(m3b0.ML <- glmer (biCat2 ~ (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (1 | ID) + (1 | display)

   Data: df2[df2$study == "mturk", ]

   AIC   BIC logLik deviance

 12088 12111  -6041    12082

Random effects:

 Groups  Name        Variance Std.Dev.

 ID      (Intercept)  0.37889 0.61554

 display (Intercept) 16.04329 4.00541

Number of obs: 15009, groups: ID, 277; display, 41



Fixed effects:

            Estimate Std. Error z value Pr(>|z|)

(Intercept)   2.1141     0.6404   3.301 0.000963 ***

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>

> #Check if full model is better than null model at accounting for variance.

> anova(m3b.ML,m3b0.ML)

Data: [

Data: df2

Data: df2$study == "mturk"

Data:

Models:

m3b0.ML: biCat2 ~ (1 | ID) + (1 | display)

m3b.ML: biCat2 ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

        Df   AIC   BIC  logLik  Chisq Chi Df Pr(>Chisq)

m3b0.ML  3 12088 12111 -6041.1

m3b.ML  12 11585 11676 -5780.3 521.58      9  < 2.2e-16 ***

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>

> #Continent

> print(m3b1.ML <- glmer (biCat2 ~ (gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (gender + cAge)^2 + (1 | ID) + (1 | display)

   Data: df2[df2$study == "mturk", ]

   AIC   BIC logLik deviance

 12087 12133  -6038    12075

Random effects:

 Groups  Name        Variance Std.Dev.

 ID      (Intercept)  0.36696 0.60577

 display (Intercept) 16.04202 4.00525

Number of obs: 15009, groups: ID, 277; display, 41



Fixed effects:

                  Estimate Std. Error z value Pr(>|z|)

(Intercept)       2.087154   0.642753   3.247 0.00117 **

gender.M-F        0.028004   0.088921   0.315 0.75282

cAge              0.017964   0.007184   2.501 0.01240 *

gender.M-F:cAge -0.013053   0.009335  -1.398 0.16202

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m3b.ML,m3b1.ML)

Data: [

Data: df2

Data: df2$study == "mturk"

Data:

Models:

m3b1.ML: biCat2 ~ (gender + cAge)^2 + (1 | ID) + (1 | display)
```

m3b.ML: biCat2 ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m3b1.ML 6 12087 12133 -6037.7

m3b.ML 12 11585 11676 -5780.3 514.75 6 < 2.2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>

> #Gender

> print(m3b2.ML <- glmer (biCat2 ~ (cont2+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (cont2 + cAge)^2 + (1 | ID) + (1 | display)

Data: df2[df2$study == "mturk",]

AIC BIC logLik deviance

11584 11645 -5784 11568

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.35268 0.59387

display (Intercept) 15.80285 3.97528

Number of obs: 14361, groups: ID, 265; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.970245 0.645525 3.052 0.00227 **

cont2.c-e 0.096883 0.130159 0.744 0.45667

cont2.n-e 0.356776 0.197575 1.806 0.07095 .

cAge -0.004361 0.013671 -0.319 0.74972

cont2.c-e:cAge 0.012278 0.014923 0.823 0.41066

cont2.n-e:cAge 0.016500 0.016800 0.982 0.32602

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m3b.ML,m3b2.ML)

Data: [

Data: df2

Data: df2$study == "mturk"

Data:

Models:

m3b2.ML: biCat2 ~ (cont2 + cAge)^2 + (1 | ID) + (1 | display)

m3b.ML: biCat2 ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m3b2.ML 8 11584 11645 -5784.2

m3b.ML 12 11585 11676 -5780.3 7.702 4 0.1031

>

> #Age

> print(m3b3.ML <- glmer (biCat2 ~ (cont2+gender)^2 + (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (cont2 + gender)^2 + (1 | ID) + (1 | display)

Data: df2[df2$study == "mturk",]

AIC BIC logLik deviance

11582 11642 -5783 11566

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.34685 0.58894

display (Intercept) 15.80332 3.97534

Number of obs: 14361, groups: ID, 265; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.87309 0.66301 2.825 0.00473 **

cont2.c-e 0.13875 0.20956 0.662 0.50789

cont2.n-e 0.85857 0.27475 3.125 0.00178 **

gender.M-F 0.16087 0.24620 0.653 0.51351

cont2.c-e:gender.M-F -0.08025 0.26615 -0.302 0.76300

cont2.n-e:gender.M-F -0.78647 0.36934 -2.129 0.03322 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m3b.ML,m3b3.ML)

Data: [

Data: df2

Data: df2$study == "mturk"

Data:

Models:

m3b3.ML: biCat2 ~ (cont2 + gender)^2 + (1 | ID) + (1 | display)

m3b.ML: biCat2 ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m3b3.ML 8 11582 11642 -5782.8

m3b.ML 12 11585 11676 -5780.3 4.9449 4 0.293

>

> print(m3c.ML <- glmer (biCat1 ~ (cont2+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat1 ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2[df2$study == "mturk",]

AIC BIC logLik deviance

15504 15595 -7740 15480

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.029531 0.17184

display (Intercept) 8.422009 2.90207

Number of obs: 14361, groups: ID, 265; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.562842 0.472992 3.304 0.000953 ***

cont2.c-e 0.077975 0.108294 0.720 0.471510

cont2.n-e 0.221757 0.146690 1.512 0.130599

gender.M-F 0.135393 0.126764 1.068 0.285487

cAge -0.002944 0.007953 -0.370 0.711316

cont2.c-e:gender.M-F -0.092714 0.137299 -0.675 0.499505

cont2.n-e:gender.M-F -0.401733 0.194467 -2.066 0.038846 *

cont2.c-e:cAge 0.005852 0.007678 0.762 0.445932

cont2.n-e:cAge 0.008160 0.008685 0.940 0.347458

gender.M-F:cAge 0.001626 0.005091 0.319 0.749369

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> print(m3c0.ML <- glmer (biCat1 ~ (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat1 ~ (1 | ID) + (1 | display)

Data: df2[df2$study == "mturk",]

AIC BIC logLik deviance

16211 16234 -8102 16205

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.0000 0.0000

display (Intercept) 8.4992 2.9153

Number of obs: 15009, groups: ID, 277; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.6731 0.4648 3.599 0.000319 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>

> #Check if full model is better than null model at accounting for variance.

> anova(m3c.ML,m3c0.ML)

Data: [

Data: df2

Data: df2$study == "mturk"

Data:

Models:

m3c0.ML: biCat1 ~ (1 | ID) + (1 | display)

m3c.ML: biCat1 ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m3c0.ML 3 16211 16234 -8102.4

m3c.ML 12 15504 15595 -7740.2 724.54 9 < 2.2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> #Continent

> print(m3c1.ML <- glmer (biCat1 ~ (gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat1 ~ (gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2[df2$study == "mturk",]

AIC BIC logLik deviance

16202 16248 -8095 16190

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.030764 0.1754

display (Intercept) 8.553617 2.9247

Number of obs: 15009, groups: ID, 277; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.654310 0.467261 3.540 0.000399 ***

gender.M-F 0.034781 0.044863 0.775 0.438185

cAge 0.005211 0.003621 1.439 0.150209

gender.M-F:cAge -0.002723 0.004710 -0.578 0.563219

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m3c.ML,m3c1.ML)

Data: [

Data: df2

Data: df2$study == "mturk"

Data:

Models:

m3c1.ML: biCat1 ~ (gender + cAge)^2 + (1 | ID) + (1 | display)

m3c.ML: biCat1 ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m3c1.ML 6 16202 16248 -8094.9

m3c.ML 12 15504 15595 -7740.2 709.49 6 < 2.2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> #Gender

> print(m3c2.ML <- glmer (biCat1 ~ (cont2+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat1 ~ (cont2 + cAge)^2 + (1 | ID) + (1 | display)

Data: df2[df2$study == "mturk",]

AIC BIC logLik deviance

15501 15562 -7743 15485

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.032009 0.17891

display (Intercept) 8.422104 2.90209

Number of obs: 14361, groups: ID, 265; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.647451 0.466520 3.531 0.000413 ***

cont2.c-e 0.019212 0.066963 0.287 0.774181

cont2.n-e 0.007780 0.101487 0.077 0.938896

cAge -0.001091 0.007027 -0.155 0.876597

cont2.c-e:cAge 0.004566 0.007675 0.595 0.551901

cont2.n-e:cAge 0.006630 0.008631 0.768 0.442399

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m3c.ML,m3c2.ML)

Data: [

Data: df2

Data: df2$study == "mturk"

Data:

Models:

m3c2.ML: biCat1 ~ (cont2 + cAge)^2 + (1 | ID) + (1 | display)

m3c.ML: biCat1 ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m3c2.ML 8 15501 15562 -7742.7

m3c.ML 12 15504 15595 -7740.2 5.0579 4 0.2814

> #Age

> print(m3c3.ML <- glmer (biCat1 ~ (cont2+gender)^2 + (1 | ID) + (1| display), family=binomial, data=df2[df2$study=="mturk",]), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat1 ~ (cont2 + gender)^2 + (1 | ID) + (1 | display)

Data: df2[df2$study == "mturk",]

AIC BIC logLik deviance

15500 15560 -7742 15484

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.031058 0.17623

display (Intercept) 8.422023 2.90207

Number of obs: 14361, groups: ID, 265; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.56708 0.47298 3.313 0.000922 ***

cont2.c-e 0.07770 0.10796 0.720 0.471696

cont2.n-e 0.25314 0.14152 1.789 0.073659 .

gender.M-F 0.13105 0.12693 1.032 0.301878

cont2.c-e:gender.M-F -0.09945 0.13723 -0.725 0.468639

cont2.n-e:gender.M-F -0.37668 0.19015 -1.981 0.047591 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m3c.ML,m3c3.ML)

Data: [

Data: df2

Data: df2$study == "mturk"

Data:

Models:

m3c3.ML: biCat1 ~ (cont2 + gender)^2 + (1 | ID) + (1 | display)

m3c.ML: biCat1 ~ (cont2 + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq) m3c3.ML 8 15500 15560 -7741.8

m3c.ML 12 15504 15595 -7740.2 3.1719 4 0.5295

>

Chapter 10:

> #Complexity new analysis breakdown

> print(m10a.ML <- glmer (complex ~ (country+enviro+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

3228 3306 -1601 3202

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 2.18299 1.47750

display (Intercept) 0.04355 0.20869

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 0.74510 0.79561 0.936 0.34901

countrye-u -1.77924 3.53599 -0.503 0.61484

enviro.u-r -2.96530 1.10456 -2.685 0.00726 **

gender.M-F -0.01124 3.06624 -0.004 0.99708

cAge -0.01019 0.07317 -0.139 0.88922

countrye-u:enviro.u-r 1.27549 1.06197 1.201 0.22973

countrye-u:gender.M-F -0.81484 1.15159 -0.708 0.47921

countrye-u:cAge -0.10034 0.35090 -0.286 0.77492

enviro.u-r:gender.M-F -2.22641 1.10932 -2.007 0.04475 *

enviro.u-r:cAge -0.15794 0.09796 -1.612 0.10691

gender.M-F:cAge -0.06850 0.29490 -0.232 0.81631

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> #Complexity new analysis Null Hypothesis

> print(m10a0.ML <- glmer (complex ~ (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

3235 3253 -1614 3229

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 3.557806 1.8862

display (Intercept) 0.043807 0.2093

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -0.2753 0.2563 -1.074 0.283

> anova(m10a.ML, m10a0.ML)

Data: df3

Models:

m10a0.ML: complex ~ (1 | ID) + (1 | display)

m10a.ML: complex ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10a.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10a0.ML 3 3234.5 3252.7 -1614.3

m10a.ML 13 3227.6 3306.3 -1600.8 26.884 10 0.002716 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> print(m10a1.ML <- glmer (complex ~ (enviro+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

3222 3277 -1602 3204

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 2.304293 1.51799

display (Intercept) 0.043559 0.20871

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 0.4796171 0.7842383 0.612 0.5408

enviro.u-r -2.6090614 1.0814035 -2.413 0.0158 *

gender.M-F -1.0296074 2.5787091 -0.399 0.6897

cAge -0.0008789 0.0744448 -0.012 0.9906

enviro.u-r:gender.M-F -1.4556737 0.9544299 -1.525 0.1272

enviro.u-r:cAge -0.1672593 0.0991842 -1.686 0.0917 .

gender.M-F:cAge -0.0649299 0.2408616 -0.270 0.7875

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m10a.ML, m10a1.ML)

Data: df3

Models:

m10a1.ML: complex ~ (enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

m10a.ML: complex ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10a.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10a1.ML 9 3222.3 3276.7 -1602.1

m10a.ML 13 3227.6 3306.3 -1600.8 2.6476 4 0.6184

> #Enviro

> print(m10a2.ML <- glmer (complex ~ (country+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (country + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

3236 3290 -1609 3218

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 2.990486 1.72930

display (Intercept) 0.043695 0.20903

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -0.77101 0.61656 -1.250 0.211

countrye-u -2.39161 3.44433 -0.694 0.487

gender.M-F -3.75139 2.98031 -1.259 0.208

cAge -0.09908 0.05329 -1.859 0.063 .

countrye-u:gender.M-F 0.61455 1.18254 0.520 0.603

countrye-u:cAge -0.22186 0.35318 -0.628 0.530

gender.M-F:cAge -0.22969 0.32185 -0.714 0.475

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m10a.ML, m10a2.ML)

Data: df3

Models:

m10a2.ML: complex ~ (country + gender + cAge)^2 + (1 | ID) + (1 | display)

m10a.ML: complex ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10a.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10a2.ML 9 3235.5 3290.0 -1608.8

m10a.ML 13 3227.6 3306.3 -1600.8 15.902 4 0.003154 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> #Gender

> print(m10a3.ML <- glmer (complex ~ (country+enviro+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (country + enviro + cAge)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

3227 3281 -1604 3209

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 2.491994 1.57861

display (Intercept) 0.043585 0.20877

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 0.761878 0.844297 0.902 0.36685

countrye-u -0.901339 2.991414 -0.301 0.76318

enviro.u-r -3.498537 1.161320 -3.013 0.00259 **

cAge -0.014112 0.077890 -0.181 0.85623

countrye-u:enviro.u-r 0.507936 0.991893 0.512 0.60859

countrye-u:cAge -0.003768 0.285845 -0.013 0.98948

enviro.u-r:cAge -0.163714 0.104632 -1.565 0.11766

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m10a.ML, m10a3.ML)

Data: df3

Models:

m10a3.ML: complex ~ (country + enviro + cAge)^2 + (1 | ID) + (1 | display)

m10a.ML: complex ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10a.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10a3.ML 9 3226.9 3281.4 -1604.5

m10a.ML 13 3227.6 3306.3 -1600.8 7.2841 4 0.1216

> #cAge

> print(m10a4.ML <- glmer (complex ~ (country+enviro+gender)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (country + enviro + gender)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

3228 3282 -1605 3210

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 2.508873 1.58394

display (Intercept) 0.043739 0.20914

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 0.8569 0.4613 1.858 0.0632 .

countrye-u -0.8012 0.6641 -1.206 0.2277

enviro.u-r -1.4981 0.6524 -2.296 0.0216 *

gender.M-F 0.4539 1.2015 0.378 0.7056

countrye-u:enviro.u-r 1.0419 1.0334 1.008 0.3133

countrye-u:gender.M-F -0.4746 1.1845 -0.401 0.6886

enviro.u-r:gender.M-F -2.1961 1.1301 -1.943 0.0520 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m10a.ML, m10a4.ML)

Data: df3

Models:

m10a4.ML: complex ~ (country + enviro + gender)^2 + (1 | ID) + (1 | display)

m10a.ML: complex ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10a.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10a4.ML 9 3227.6 3282.0 -1604.8

m10a.ML 13 3227.6 3306.3 -1600.8 7.9547 4 0.09325 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>

> ##Section 2 Analysis Chapter 10 ## Mid-Range ##

>

> #Complexity new analysis breakdown

> print(m10b.ML <- glmer (biCat2 ~ (country+enviro+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

2658 2737 -1316 2632

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.22385 0.47312

display (Intercept) 19.17776 4.37924

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 2.84523 0.78375 3.630 0.000283 ***

countrye-u -1.25203 1.33767 -0.936 0.349286

enviro.u-r -0.79026 0.40421 -1.955 0.050575 .

gender.M-F 1.48234 1.16713 1.270 0.204057

cAge 0.02072 0.02928 0.708 0.479046

countrye-u:enviro.u-r 0.69442 0.42088 1.650 0.098963 .

countrye-u:gender.M-F -0.31541 0.44098 -0.715 0.474455

countrye-u:cAge -0.10151 0.13235 -0.767 0.443090

enviro.u-r:gender.M-F -1.32919 0.43478 -3.057 0.002235 **

enviro.u-r:cAge -0.05068 0.03588 -1.413 0.157800

gender.M-F:cAge 0.09517 0.11174 0.852 0.394378

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> #Null Hypothesis

> print(m10b0.ML <- glmer (biCat2 ~ (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

2657 2675 -1325 2651

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.36068 0.60056

display (Intercept) 19.16920 4.37826

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 2.4082 0.7216 3.337 0.000845 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>

> #Check if full model is better than null model at accounting for variance.

> anova(m10b.ML, m10b0.ML)

Data: df3

Models:

m10b0.ML: biCat2 ~ (1 | ID) + (1 | display)

m10b.ML: biCat2 ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10b.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10b0.ML 3 2656.6 2674.7 -1325.3

m10b.ML 13 2658.4 2737.1 -1316.2 18.163 10 0.05228 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>

>

> ##Checking individual variables

>

> #Country

> print(m10b1.ML <- glmer (biCat2 ~ (enviro+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

2653 2708 -1318 2635

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.24184 0.49177

display (Intercept) 19.18063 4.37957

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 2.75423 0.78153 3.524 0.000425 ***

enviro.u-r -0.62029 0.39776 -1.559 0.118892

gender.M-F 0.71029 0.95595 0.743 0.457473

cAge 0.02250 0.02972 0.757 0.449074

enviro.u-r:gender.M-F -0.96796 0.37394 -2.589 0.009639 **

enviro.u-r:cAge -0.05280 0.03652 -1.446 0.148299

gender.M-F:cAge 0.05432 0.08873 0.612 0.540418

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m10b.ML, m10b1.ML)

Data: df3

Models:

m10b1.ML: biCat2 ~ (enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

m10b.ML: biCat2 ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10b.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10b1.ML 9 2653.3 2707.7 -1317.6

m10b.ML 13 2658.4 2737.1 -1316.2 2.8553 4 0.5823

>

> #Enviro

> print(m10b2.ML <- glmer (biCat2 ~ (country+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (country + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

2665 2719 -1323 2647

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.32834 0.57301

display (Intercept) 19.17216 4.37860

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 2.38753 0.75077 3.180 0.00147 **

countrye-u -0.74613 1.25566 -0.594 0.55237

gender.M-F -0.64528 1.08848 -0.593 0.55330

cAge -0.01210 0.01952 -0.620 0.53533

countrye-u:gender.M-F 0.35891 0.44536 0.806 0.42031

countrye-u:cAge -0.07373 0.12908 -0.571 0.56786

gender.M-F:cAge -0.01323 0.11904 -0.111 0.91151

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m10b.ML, m10b2.ML)

Data: df3

Models:

m10b2.ML: biCat2 ~ (country + gender + cAge)^2 + (1 | ID) + (1 | display)

m10b.ML: biCat2 ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10b.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10b2.ML 9 2664.8 2719.2 -1323.4

m10b.ML 13 2658.4 2737.1 -1316.2 14.372 4 0.006199 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>

> #Gender

> print(m10b3.ML <- glmer (biCat2 ~ (country+enviro+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (country + enviro + cAge)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

2661 2715 -1321 2643

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.29412 0.54233

display (Intercept) 19.16705 4.37802

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 2.870125 0.795285 3.609 0.000307 ***

countrye-u -0.264761 1.150822 -0.230 0.818043

enviro.u-r -0.966970 0.433731 -2.229 0.025786 *

cAge 0.018372 0.031930 0.575 0.565044

countrye-u:enviro.u-r 0.176342 0.399588 0.441 0.658988

countrye-u:cAge -0.009463 0.109533 -0.086 0.931151

enviro.u-r:cAge -0.045606 0.039043 -1.168 0.242766

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m10b.ML, m10b3.ML)

Data: df3

Models:

m10b3.ML: biCat2 ~ (country + enviro + cAge)^2 + (1 | ID) + (1 | display)

m10b.ML: biCat2 ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10b.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10b3.ML 9 2660.5 2715.0 -1321.3

m10b.ML 13 2658.4 2737.1 -1316.2 10.122 4 0.03843 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>

> #cAge

> print(m10b4.ML <- glmer (biCat2 ~ (country+enviro+gender)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (country + enviro + gender)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

2653 2708 -1318 2635

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.24418 0.49415

display (Intercept) 19.17624 4.37907

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 2.6597 0.7370 3.609 0.000308 ***

countrye-u -0.2651 0.2529 -1.049 0.294360

enviro.u-r -0.3421 0.2471 -1.384 0.166236

gender.M-F 0.5355 0.4539 1.180 0.238100

countrye-u:enviro.u-r 0.5770 0.3895 1.481 0.138504

countrye-u:gender.M-F -0.3177 0.4431 -0.717 0.473320

enviro.u-r:gender.M-F -1.1892 0.4228 -2.813 0.004913 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m10b.ML, m10b4.ML)

Data: df3

Models:

m10b4.ML: biCat2 ~ (country + enviro + gender)^2 + (1 | ID) + (1 | display)

m10b.ML: biCat2 ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10b.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10b4.ML 9 2653.5 2707.9 -1317.7

m10b.ML 13 2658.4 2737.1 -1316.2 3.051 4 0.5493

>

> ##Section 3 Analysis Chapter 10 ## Equalized Mid-Range ##

>

> #Mid-Range new analysis breakdown

```
> print(m10c.ML <- glmer (biCat1 ~ (country+enviro+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat1 ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |      display)

   Data: df3

  AIC  BIC logLik deviance

 3331 3409  -1652     3305

Random effects:

 Groups  Name        Variance Std.Dev.

 ID      (Intercept) 0.047364 0.21763

 display (Intercept) 5.877259 2.42431

Number of obs: 3132, groups: ID, 58; display, 41


Fixed effects:

                     Estimate Std. Error z value Pr(>|z|)

(Intercept)           1.80186    0.44562   4.044 5.27e-05 ***

countrye-u           -1.12885    0.86793  -1.301 0.1934

enviro.u-r           -0.23298    0.26838  -0.868 0.3853

gender.M-F            0.94719    0.75533   1.254 0.2098

cAge                  0.03744    0.01971   1.900 0.0575 .

countrye-u:enviro.u-r  0.32855    0.27140   1.211   0.2261

countrye-u:gender.M-F -0.07080    0.28371  -0.250   0.8029

countrye-u:cAge       -0.10876    0.08586  -1.267   0.2053

enviro.u-r:gender.M-F -0.46600    0.27987  -1.665   0.0959 .

enviro.u-r:cAge       -0.02973    0.02387  -1.245 0.2130

gender.M-F:cAge        0.06940    0.07249   0.957   0.3384

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>

> #Null Hypothesis

> print(m10c0.ML <- glmer (biCat1 ~ (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat1 ~ (1 | ID) + (1 | display)

   Data: df3

  AIC  BIC logLik deviance

 3318 3336  -1656     3312

Random effects:

 Groups  Name        Variance Std.Dev.

 ID      (Intercept) 0.068699 0.26211

 display (Intercept) 5.879760 2.42482

Number of obs: 3132, groups: ID, 58; display, 41


Fixed effects:

            Estimate Std. Error z value Pr(>|z|)

(Intercept)   1.4898     0.3943   3.778 0.000158 ***

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>

> #Check if full model is better than null model at accounting for variance.

> anova(m10c.ML, m10c0.ML)

Data: df3

Models:

m10c0.ML: biCat1 ~ (1 | ID) + (1 | display)

m10c.ML: biCat1 ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10c.ML:     display)

         Df    AIC    BIC  logLik  Chisq Chi Df Pr(>Chisq)

m10c0.ML  3 3318.0 3336.2 -1656.0

m10c.ML  13 3330.6 3409.2 -1652.3 7.4579     10     0.6816

> #Country
```

> print(m10c1.ML <- glmer (biCat1 ~ (enviro+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat1 ~ (enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

3325 3379 -1653 3307

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.053239 0.23074

display (Intercept) 5.877974 2.42445

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.77090 0.44311 3.997 6.43e-05 ***

enviro.u-r -0.16986 0.26273 -0.647 0.5180

gender.M-F 0.33483 0.61642 0.543 0.5870

cAge 0.03624 0.01986 1.825 0.0681 .

enviro.u-r:gender.M-F -0.31801 0.24078 -1.321 0.1866

enviro.u-r:cAge -0.02874 0.02416 -1.190 0.2341

gender.M-F:cAge 0.01333 0.05723 0.233 0.8158

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m10c.ML, m10c1.ML)

Data: df3

Models:

m10c1.ML: biCat1 ~ (enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

m10c.ML: biCat1 ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10c1.ML 9 3324.7 3379.1 -1653.3

m10c.ML 13 3330.6 3409.2 -1652.3 2.1268 4 0.7125

> #Enviro

> print(m10c2.ML <- glmer (biCat1 ~ (country+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat1 ~ (country + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

3327 3381 -1654 3309

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.059591 0.24411

display (Intercept) 5.878520 2.42457

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.64401 0.41397 3.971 7.15e-05 ***

countrye-u -0.46709 0.74718 -0.625 0.532

gender.M-F 0.16451 0.64749 0.254 0.799

cAge 0.01835 0.01182 1.552 0.121

countrye-u:gender.M-F 0.12438 0.26428 0.471 0.638

countrye-u:cAge -0.04744 0.07679 -0.618 0.537

gender.M-F:cAge 0.02127 0.07079 0.300 0.764

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m10c.ML, m10c2.ML)

Data: df3

Models:

m10c2.ML: biCat1 ~ (country + gender + cAge)^2 + (1 | ID) + (1 | display)

m10c.ML: biCat1 ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10c.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10c2.ML 9 3327.0 3381.4 -1654.5

m10c.ML 13 3330.6 3409.2 -1652.3 4.3892 4 0.3559

> #Gender

> print(m10c3.ML <- glmer (biCat1 ~ (country+enviro+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat1 ~ (country + enviro + cAge)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

3326 3380 -1654 3308

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.05599 0.23662

display (Intercept) 5.87742 2.42434

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.81759 0.44795 4.058 4.96e-05 ***

countrye-u -0.64365 0.70437 -0.914 0.3608

enviro.u-r -0.25844 0.27113 -0.953 0.3405

cAge 0.03660 0.02021 1.811 0.0702 .

countrye-u:enviro.u-r 0.12967 0.24393 0.532 0.5950

countrye-u:cAge -0.06680 0.06704 -0.996 0.3191

enviro.u-r:cAge -0.02665 0.02444 -1.090 0.2756

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m10c.ML, m10c3.ML)

Data: df3

Models:

m10c3.ML: biCat1 ~ (country + enviro + cAge)^2 + (1 | ID) + (1 | display)

m10c.ML: biCat1 ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10c.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10c3.ML 9 3325.7 3380.1 -1653.8

m10c.ML 13 3330.6 3409.2 -1652.3 3.1161 4 0.5386

> #cAge

> print(m10c4.ML <- glmer (biCat1 ~ (country+enviro+gender)^2 + (1 | ID) + (1| display), family=binomial, data=df3), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat1 ~ (country + enviro + gender)^2 + (1 | ID) + (1 | display)

Data: df3

AIC BIC logLik deviance

3328 3382 -1655 3310

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.06183 0.24866

display (Intercept) 5.87953 2.42477

Number of obs: 3132, groups: ID, 58; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.45799 0.40717 3.581 0.000343 ***

countrye-u -0.07553 0.16674 -0.453 0.650564

enviro.u-r 0.03973 0.16305 0.244 0.807474

gender.M-F 0.26708 0.29666 0.900 0.367963

countrye-u:enviro.u-r 0.21691 0.25633 0.846 0.397427

countrye-u:gender.M-F -0.07592 0.29038 -0.261 0.793740

enviro.u-r:gender.M-F -0.36499 0.27756 -1.315 0.188510

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m10c.ML, m10c4.ML)

Data: df3

Models:

m10c4.ML: biCat1 ~ (country + enviro + gender)^2 + (1 | ID) + (1 | display)

m10c.ML: biCat1 ~ (country + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m10c.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m10c4.ML 9 3327.8 3382.2 -1654.9

m10c.ML 13 3330.6 3409.2 -1652.3 5.1796 4 0.2694

Chapter 11:

>

> #Section 1 Chapter 11

> print(m11a.ML <- lmer (complex ~ (CNS+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (CNS + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

1521 1569 -751.5 1503

Random effects:

Groups Name Variance Std.Dev.

display (Intercept) 0.098021 0.31308

ID (Intercept) 0.026215 0.16191

Number of obs: 1620, groups: display, 41; ID, 30

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 0.40201 8.24014 0.049 0.961

CNS -0.02996 0.16143 -0.186 0.853

gender.M-F 0.52900 2.33035 0.227 0.820

cAge 0.12747 0.70185 0.182 0.856

CNS:gender.M-F 0.01793 0.02023 0.887 0.375

CNS:cAge -0.00181 0.01368 -0.132 0.895

gender.M-F:cAge 0.13664 0.19381 0.705 0.481

>

> #

> df2b <- df2[df2$enviro=="urban" | df2$enviro=="rural",]

> #Section 1 Chapter 11

> print(m11a.ML <- lmer (complex ~ (CNS+enviro+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (CNS + enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

1520 1590 -747.2 1494

Random effects:

Groups Name Variance Std.Dev.

display (Intercept) 0.098476 0.31381

ID (Intercept) 0.000000 0.00000

Number of obs: 1620, groups: display, 41; ID, 30

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -6.090351 8.109564 -0.751 0.45265

CNS 0.191186 0.175787 1.088 0.27677

enviro.u-r -8.252392 3.167436 -2.605 0.00918 **

gender.M-F 1.329463 2.363662 0.562 0.57380

cAge -0.447413 0.696855 -0.642 0.52084

CNS:enviro.u-r 0.008920 0.018993 0.470 0.63862

CNS:gender.M-F 0.009572 0.019178 0.499 0.61770

CNS:cAge 0.017595 0.015136 1.163 0.24504

enviro.u-r:gender.M-F -0.095031 0.325191 -0.292 0.77011

enviro.u-r:cAge -0.658852 0.252660 -2.608 0.00912 **

gender.M-F:cAge 0.157865 0.197606 0.799 0.42436

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>

> #Null Model

> print(m11a0.ML <- lmer (complex ~ (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

5881 5901 -2937 5875

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 3.052674 1.74719

display (Intercept) 0.067999 0.26077

Number of obs: 5929, groups: ID, 110; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -0.7686 0.1764 -4.358 1.31e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m11a.ML, m11a0.ML)

Data: df2

Models:

m11a0.ML: complex ~ (1 | ID) + (1 | display)

m11a.ML: complex ~ (CNS + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m11a.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m11a0.ML 3 5880.9 5900.9 -2937.44

m11a.ML 13 1520.4 1590.4 -747.19 4380.5 10 < 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>

>

> #CNS

> print(m11a1.ML <- lmer (complex ~ (enviro+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

5871 5932 -2927 5853

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 2.489167 1.57771

display (Intercept) 0.067921 0.26062

Number of obs: 5929, groups: ID, 110; display, 41

```
Fixed effects:

                 Estimate Std. Error z value
Pr(>|z|)

(Intercept)          -0.48346    0.28331  -1.706
0.0879 .

enviro.u-r           -0.53288    0.40550  -1.314
0.1888

gender.M-F            0.25483    0.43008   0.592
0.5535

cAge                -0.03914    0.01592  -2.459
0.0139 *

enviro.u-r:gender.M-F -0.86054    0.68580  -
1.255   0.2096

enviro.u-r:cAge       0.02090    0.02195   0.952
0.3411

gender.M-F:cAge       0.05057    0.02297
2.201   0.0277 *

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05
'.' 0.1 ' ' 1

> anova(m11a.ML, m11a1.ML)

Data: df2

Models:

m11a1.ML: complex ~ (enviro + gender +
cAge)^2 + (1 | ID) + (1 | display)

m11a.ML: complex ~ (CNS + enviro + gender
+ cAge)^2 + (1 | ID) + (1 |

m11a.ML:     display)

       Df    AIC    BIC   logLik  Chisq Chi Df
Pr(>Chisq)

m11a1.ML  9 5871.5 5931.7 -2926.75

m11a.ML  13 1520.4 1590.4  -747.19 4359.1
4  < 2.2e-16 ***

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05
'.' 0.1 ' ' 1

> #enviro

> print(m11a2.ML <- lmer (complex ~
(CNS+gender+cAge)^2 + (1 | ID) + (1| display),
family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the
Laplace approximation

Formula: complex ~ (CNS + gender + cAge)^2
+ (1 | ID) + (1 | display)

   Data: df2

  AIC  BIC logLik deviance

 1521 1569 -751.5     1503

Random effects:

 Groups  Name        Variance Std.Dev.

 display (Intercept) 0.098021 0.31308

 ID      (Intercept) 0.026215 0.16191

Number of obs: 1620, groups: display, 41; ID,
30


Fixed effects:

              Estimate Std. Error z value Pr(>|z|)

(Intercept)      0.40201    8.24014   0.049
0.961

CNS            -0.02996    0.16143  -0.186
0.853

gender.M-F       0.52900    2.33035   0.227
0.820

cAge            0.12747    0.70185   0.182    0.856

CNS:gender.M-F   0.01793    0.02023   0.887
0.375

CNS:cAge       -0.00181    0.01368  -0.132
0.895

gender.M-F:cAge  0.13664    0.19381   0.705
0.481

> anova(m11a.ML, m11a2.ML)

Data: df2

Models:

m11a2.ML: complex ~ (CNS + gender +
cAge)^2 + (1 | ID) + (1 | display)

m11a.ML: complex ~ (CNS + enviro + gender
+ cAge)^2 + (1 | ID) + (1 |

m11a.ML:     display)

        Df    AIC    BIC  logLik Chisq Chi Df
Pr(>Chisq)

m11a2.ML  9 1520.9 1569.4 -751.46

m11a.ML  13 1520.4 1590.5 -747.19 8.537      4
0.07377 .

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05
'.' 0.1 ' ' 1

>

> #gender

> print(m11a3.ML <- lmer (complex ~
(CNS+enviro+cAge)^2 + (1 | ID) + (1| display),
family=binomial, data=df2), cor=FALSE)
```

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (CNS + enviro + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

1514 1563 -748.1 1496

Random effects:

Groups Name Variance Std.Dev.

display (Intercept) 9.8018e-02 3.1308e-01

ID (Intercept) 5.8322e-12 2.4150e-06

Number of obs: 1620, groups: display, 41; ID, 30

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -8.42841 7.85389 -1.073 0.28320

CNS 0.25417 0.16628 1.529 0.12637

enviro.u-r -8.71276 3.07417 -2.834 0.00459 **

cAge -0.64097 0.67771 -0.946 0.34425

CNS:enviro.u-r 0.00969 0.01788 0.542 0.58786

CNS:cAge 0.02286 0.01440 1.587 0.11254

enviro.u-r:cAge -0.68953 0.24567 -2.807 0.00501 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m11a.ML, m11a3.ML)

Data: df2

Models:

m11a3.ML: complex ~ (CNS + enviro + cAge)^2 + (1 | ID) + (1 | display)

m11a.ML: complex ~ (CNS + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m11a.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m11a3.ML 9 1514.2 1562.7 -748.10

m11a.ML 13 1520.4 1590.5 -747.19 1.8182 4 0.7691

> #Age

> print(m11a4.ML <- lmer (complex ~ (CNS+enviro+gender)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (CNS + enviro + gender)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

1520 1568 -750.8 1502

Random effects:

Groups Name Variance Std.Dev.

display (Intercept) 0.097944 0.31296

ID (Intercept) 0.020296 0.14247

Number of obs: 1620, groups: display, 41; ID, 30

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -1.048309 0.553459 -1.894 0.0582 .

CNS -0.009008 0.012328 -0.731 0.4650

enviro.u-r -0.241660 0.916017 -0.264 0.7919

gender.M-F -0.643276 1.028041 -0.626 0.5315

CNS:enviro.u-r 0.003181 0.018750 0.170 0.8653

CNS:gender.M-F 0.012775 0.020059 0.637 0.5242

enviro.u-r:gender.M-F -0.269292 0.306117 -0.880 0.3790

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m11a.ML, m11a4.ML)

Data: df2

Models:

m11a4.ML: complex ~ (CNS + enviro + gender)^2 + (1 | ID) + (1 | display)

m11a.ML: complex ~ (CNS + enviro + gender + cAge)^2 + (1 | ID) + (1 |

m11a.ML: display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m11a4.ML 9 1519.6 1568.2 -750.82

m11a.ML 13 1520.4 1590.5 -747.19 7.2646 4 0.1225

>

> #Section 2 Chapter 11

> #Full Model

> print(m11b.ML <- lmer (biCat2 ~ (CNS+enviro+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (CNS + enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

1319 1389 -646.6 1293

Random effects:

Groups Name Variance Std.Dev.

display (Intercept) 1.5942e+01 3.9927e+00

ID (Intercept) 2.7295e-14 1.6521e-07

Number of obs: 1620, groups: display, 41; ID, 30

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -2.8116008 8.8367434 -0.318 0.750

CNS 0.1149753 0.1909523 0.602 0.547

enviro.u-r -2.3327375 3.5975163 -0.648 0.517

gender.M-F 0.7290312 2.4636865 0.296 0.767

cAge -0.3991885 0.7552530 -0.528 0.597

CNS:enviro.u-r 0.0024207 0.0205132 0.118 0.906

CNS:gender.M-F 0.0009214 0.0208447 0.044 0.965

CNS:cAge 0.0099251 0.0164019 0.605 0.545

enviro.u-r:gender.M-F 0.2408672 0.3420841 0.704 0.481

enviro.u-r:cAge -0.1678745 0.2888003 -0.581 0.561

gender.M-F:cAge 0.0870790 0.2080412 0.419 0.676

> #Null Model

> print(m11b0.ML <- lmer (biCat2 ~ (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

4924 4944 -2459 4918

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.28953 0.53808

display (Intercept) 21.66589 4.65466

Number of obs: 5929, groups: ID, 110; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 2.3973 0.7572 3.166 0.00154 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m11b.ML, m11b0.ML)

Data: df2

Models:

m11b0.ML: biCat2 ~ (1 | ID) + (1 | display)

m11b.ML: biCat2 ~ (CNS + enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m11b0.ML 3 4923.6 4943.7 -2458.81

m11b.ML 13 1319.3 1389.4 -646.65 3624.3 10 < 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> #CNS

> print(m11b1.ML <- lmer (biCat2 ~ (enviro+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

4917 4978 -2450   4899

Random effects:

Groups Name   Variance Std.Dev.

ID   (Intercept) 0.22297 0.47219

display (Intercept) 21.66710 4.65479

Number of obs: 5929, groups: ID, 110; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept)   2.540495   0.761465   3.336 0.000849 ***

enviro.u-r   -0.262778   0.148109 -1.774 0.076026 .

gender.M-F   0.077208   0.157916   0.489 0.624902

cAge   -0.006049   0.005478 -1.104 0.269538

enviro.u-r:gender.M-F -0.373697   0.251208 -1.488 0.136856

enviro.u-r:cAge   -0.002444   0.007825 -0.312 0.754765

gender.M-F:cAge   0.009764   0.008261   1.182 0.237241

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m11b.ML, m11b1.ML)

Data: df2

Models:

m11b1.ML: biCat2 ~ (enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

m11b.ML: biCat2 ~ (CNS + enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Df   AIC   BIC logLik Chisq Chi Df Pr(>Chisq)

m11b1.ML 9 4917.4 4977.6 -2449.70

m11b.ML 13 1319.3 1389.4 -646.65 3606.1 4 < 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>

> #Enviro

> print(m11b2.ML <- lmer (biCat2 ~ (CNS+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (CNS + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

1313 1361 -647.3   1295

Random effects:

Groups Name   Variance Std.Dev.

display (Intercept) 15.91   3.9887

ID   (Intercept) 0.00   0.0000

Number of obs: 1620, groups: display, 41; ID, 30

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept)   -1.226847   8.337419 -0.147 0.883

CNS   0.069970   0.162114   0.432 0.666

gender.M-F   -0.283149   2.279149 -0.124 0.901

cAge   -0.260867   0.707475 -0.369 0.712

CNS:gender.M-F   0.004977   0.020052   0.248 0.804

CNS:cAge   0.006147   0.013734   0.448 0.654

gender.M-F:cAge 0.011254 0.190974 0.059 0.953

> anova(m11b.ML, m11b2.ML)

Data: df2

Models:

m11b2.ML: biCat2 ~ (CNS + gender + cAge)^2 + (1 | ID) + (1 | display)

m11b.ML: biCat2 ~ (CNS + enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m11b2.ML 9 1312.7 1361.2 -647.34

m11b.ML 13 1319.3 1389.4 -646.65 1.3898 4 0.846

>

> #Gender

> print(m11b3.ML <- lmer (biCat2 ~ (CNS+enviro+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (CNS + enviro + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

1313 1361 -647.3 1295

Random effects:

Groups Name Variance Std.Dev.

display (Intercept) 15.913 3.9891

ID (Intercept) 0.000 0.0000

Number of obs: 1620, groups: display, 41; ID, 30

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -3.094661 8.601056 -0.360 0.719

CNS 0.125095 0.182685 0.685 0.493

enviro.u-r -2.326856 3.462235 -0.672 0.502

cAge -0.435046 0.737781 -0.590 0.555

CNS:enviro.u-r 0.007426 0.019117 0.388 0.698

CNS:cAge 0.011213 0.015777 0.711 0.477

enviro.u-r:cAge -0.155693 0.279913 -0.556 0.578

> anova(m11b.ML, m11b3.ML)

Data: df2

Models:

m11b3.ML: biCat2 ~ (CNS + enviro + cAge)^2 + (1 | ID) + (1 | display)

m11b.ML: biCat2 ~ (CNS + enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m11b3.ML 9 1312.5 1361.0 -647.26

m11b.ML 13 1319.3 1389.4 -646.65 1.2287 4 0.8734

>

> #Age

> print(m11b4.ML <- lmer (biCat2 ~ (CNS+enviro+gender)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (CNS + enviro + gender)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

1312 1361 -647.1 1294

Random effects:

Groups Name Variance Std.Dev.

display (Intercept) 15.921 3.9902

ID (Intercept) 0.000 0.0000

Number of obs: 1620, groups: display, 41; ID, 30

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 1.7782932 0.8791319 2.023 0.0431 *

CNS 0.0008933 0.0130738 0.068 0.9455

enviro.u-r -0.1678150 0.9482410 -0.177 0.8595 gender.M-F -0.2741357 1.0435787 -0.263 0.7928

CNS:enviro.u-r -0.0016088 0.0193384 -0.083 0.9337

CNS:gender.M-F 0.0009749 0.0203744 0.048 0.9618

enviro.u-r:gender.M-F 0.1729097 0.3099126 0.558 0.5769

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m11b.ML, m11b4.ML)

Data: df2

Models:

m11b4.ML: biCat2 ~ (CNS + enviro + gender)^2 + (1 | ID) + (1 | display)

m11b.ML: biCat2 ~ (CNS + enviro + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m11b4.ML 9 1312.1 1360.7 -647.07

m11b.ML 13 1319.3 1389.4 -646.65 0.8478 4 0.9319

>

Chapter 12:

> # Chapter 12 Analysis

>

> #Section 1 complexity model

>

> #Full Model

> print(m12a.ML <- glmer (complex ~ (continent+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (continent + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

6927 7009 -3452 6903

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 2.595648 1.61110

display (Intercept) 0.060443 0.24585

Number of obs: 7009, groups: ID, 130; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -0.25417 0.23946 -1.062 0.28848

continentafrica 0.24767 1.17521 0.211 0.83308

continentcentralasia -0.74184 0.77652 -0.955 0.33941

gender.M-F -1.12354 0.66595 -1.687 0.09158 .

cAge -0.03273 0.01118 -2.928 0.00341 **

continentafrica:gender.M-F 1.27048 0.86594 1.467 0.14233

continentcentralasia:gender.M-F 2.85369 1.37910 2.069 0.03852 *

continentafrica:cAge 0.15850 0.16986 0.933 0.35074

continentcentralasia:cAge -0.20062 0.10603 -1.892 0.05848 .

gender.M-F:cAge 0.06782 0.02347 2.890 0.00386 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>

> #Null Model

> print(m12a0.ML <- glmer (complex ~ (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

6929 6950 -3462 6923

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 3.100711 1.76088

display (Intercept) 0.060408 0.24578

Number of obs: 7009, groups: ID, 130; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -0.7229 0.1635 -4.42 9.85e-06 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m12a.ML, m12a0.ML)

Data: df2

Models:

m12a0.ML: complex ~ (1 | ID) + (1 | display)

m12a.ML: complex ~ (continent + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m12a0.ML 3 6929.4 6950.0 -3461.7

m12a.ML 12 6927.2 7009.5 -3451.6 20.217 9 0.01662 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>

> #Continent

> print(m12a1.ML <- glmer (complex ~ (gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

6926 6967 -3457 6914

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 2.887618 1.69930

display (Intercept) 0.060394 0.24575

Number of obs: 7009, groups: ID, 130; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -0.57477 0.19261 -2.984 0.00284 **

gender.M-F -0.37425 0.32557 -1.149 0.25034

cAge -0.02666 0.01119 -2.381 0.01726 *

gender.M-F:cAge 0.05280 0.02051 2.574 0.01005 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m12a.ML, m12a1.ML)

Data: df2

Models:

m12a1.ML: complex ~ (gender + cAge)^2 + (1 | ID) + (1 | display)

m12a.ML: complex ~ (continent + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m12a1.ML 6 6926.3 6967.4 -3457.1

m12a.ML 12 6927.2 7009.5 -3451.6 11.051 6 0.08681 .

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>

> #gender

> print(m12a2.ML <- glmer (complex ~ (continent+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (continent + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

6930 6985 -3457 6914

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 2.830802 1.68250

display (Intercept) 0.060442 0.24585

Number of obs: 7009, groups: ID, 130; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -0.357429 0.232651 -1.536 0.1245

continentafrica 0.450438 1.212685 0.371 0.7103

continentcentralasia 0.006794 0.651953 0.010 0.9917

cAge -0.018355 0.010063 -1.824 0.0681 .

continentafrica:cAge 0.183907 0.175940 1.045 0.2959

continentcentralasia:cAge -0.157041 0.109646 -1.432 0.1521

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(m12a.ML, m12a2.ML)

Data: df2

Models:

m12a2.ML: complex ~ (continent + cAge)^2 + (1 | ID) + (1 | display)

m12a.ML: complex ~ (continent + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m12a2.ML 8 6929.9 6984.7 -3456.9

m12a.ML 12 6927.2 7009.5 -3451.6 10.687 4 0.03031 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>

> #Age

> print(m12a3.ML <- glmer (complex ~ (continent+gender)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: complex ~ (continent + gender)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

6934 6989 -3459 6918

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 2.947763 1.71691

display (Intercept) 0.060423 0.24581

Number of obs: 7009, groups: ID, 130; display, 4

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -0.40339 0.24842 -1.624 0.104

continentafrica -0.42825 0.40818 -1.049 0.294

continentcentralasia -0.62813 0.82312 -0.763 0.445

gender.M-F -0.43909 0.61468 -0.714 0.475

continentafrica:gender.M-F 0.08613 0.76513 0.113 0.910

continentcentralasia:gender.M-F 2.07441 1.42198 1.459 0.145

> anova(m12a.ML, m12a3.ML)

Data: df2

Models:

m12a3.ML: complex ~ (continent + gender)^2 + (1 | ID) + (1 | display)

m12a.ML: complex ~ (continent + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m12a3.ML 8 6933.7 6988.6 -3458.9

m12a.ML 12 6927.2 7009.5 -3451.6 14.537 4 0.005765 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>

> #Section 2 mid-range model

>

> #Full Model

> print(m12b.ML <- glmer (biCat2 ~ (continent+gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (continent + gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

5813 5896 -2895 5789

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.24517 0.49515

display (Intercept) 23.00364 4.79621

Number of obs: 7009, groups: ID, 130; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 2.634483 0.781922 3.369 0.000754 ***

continentafrica 0.345407 0.424041 0.815 0.415324

continentcentralasia -0.613243 0.289938 -2.115 0.034423 *

gender.M-F -0.350755 0.243233 -1.442 0.149287

cAge -0.009035 0.004059 -2.226 0.026016 *

continentafrica:gender.M-F 0.422205 0.317572 1.329 0.183690

continentcentralasia:gender.M-F 0.721947 0.513392 1.406 0.159656

continentafrica:cAge 0.082917 0.061186 1.355 0.175365

continentcentralasia:cAge -0.068066 0.040039 -1.700 0.089134 .

gender.M-F:cAge 0.022346 0.008715 2.564 0.010344 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>

>

> #Null Model

> print(m12b0.ML <- glmer (biCat2 ~ (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

5812 5832 -2903 5806

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.29733 0.54528

display (Intercept) 22.99829 4.79565

Number of obs: 7009, groups: ID, 130; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 2.487 0.779 3.193 0.00141 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m12b.ML, m12b0.ML)

Data: df2

Models:

m12b0.ML: biCat2 ~ (1 | ID) + (1 | display)

m12b.ML: biCat2 ~ (continent + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m12b0.ML 3 5811.7 5832.3 -2902.9

m12b.ML 12 5813.4 5895.7 -2894.7 16.339 9 0.06012 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>

> #Continent

> print(m12b1.ML <- glmer (biCat2 ~ (gender+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (gender + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

5812 5853 -2900 5800

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.27695 0.52626

display (Intercept) 22.99926 4.79575

Number of obs: 7009, groups: ID, 130; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 2.530740 0.779964 3.245 0.00118 **

gender.M-F -0.103683 0.119439 -0.868 0.38535

cAge -0.007381 0.004017 -1.837 0.06616 .

gender.M-F:cAge 0.016522 0.007563 2.185 0.02892 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m12b.ML, m12b1.ML)

Data: df2

Models:

m12b1.ML: biCat2 ~ (gender + cAge)^2 + (1 | ID) + (1 | display)

m12b.ML: biCat2 ~ (continent + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m12b1.ML 6 5811.6 5852.8 -2899.8

m12b.ML 12 5813.4 5895.7 -2894.7 10.241 6 0.1149

>

> #gender

> print(m12b2.ML <- glmer (biCat2 ~ (continent+cAge)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (continent + cAge)^2 + (1 | ID) + (1 | display)

Data: df2

AIC BIC logLik deviance

5813 5868 -2898 5797

Random effects:

Groups Name Variance Std.Dev.

ID (Intercept) 0.26801 0.5177

display (Intercept) 23.00662 4.7965

Number of obs: 7009, groups: ID, 130; display, 41

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 2.602226 0.781556 3.330 0.00087 ***

continentafrica 0.430331 0.431826 0.997 0.31899

continentcentralasia -0.443547 0.240712 -1.843 0.06538 .

cAge -0.004413 0.003651 -1.209 0.22682

continentafrica:cAge 0.092352 0.062634 1.474 0.14035

continentcentralasia:cAge -0.055322 0.041032 -1.348 0.17757

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m12b.ML, m12b2.ML)

Data: df2

Models:

m12b2.ML: biCat2 ~ (continent + cAge)^2 + (1 | ID) + (1 | display)

m12b.ML: biCat2 ~ (continent + gender + cAge)^2 + (1 | ID) + (1 | display)

Df AIC BIC logLik Chisq Chi Df Pr(>Chisq)

m12b2.ML 8 5812.8 5867.6 -2898.4

m12b.ML 12 5813.4 5895.7 -2894.7 7.3568 4 0.1182

>

> #Age

```
> print(m12b3.ML <- glmer (biCat2 ~ (continent+gender)^2 + (1 | ID) + (1| display), family=binomial, data=df2), cor=FALSE)

Generalized linear mixed model fit by the Laplace approximation

Formula: biCat2 ~ (continent + gender)^2 + (1 | ID) + (1 | display)

   Data: df2

  AIC  BIC logLik deviance

 5817 5872  -2901     5801

Random effects:

 Groups  Name        Variance Std.Dev.

 ID      (Intercept)  0.28171 0.53076

 display (Intercept) 22.99793 4.79562

Number of obs: 7009, groups: ID, 130; display, 41



Fixed effects:

                         Estimate Std. Error z value Pr(>|z|)

(Intercept)               2.59067    0.78202   3.313 0.000924 ***

continentafrica          -0.09176    0.14957  -0.613 0.539554

continentcentralasia     -0.58345    0.30272  -1.927 0.053936 .

gender.M-F               -0.10959    0.22358  -0.490 0.624014

continentafrica:gender.M-F       0.00970    0.27883   0.035 0.972248

continentcentralasia:gender.M-F  0.45834    0.52249   0.877 0.380360

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(m12b.ML, m12b3.ML)

Data: df2

Models:

m12b3.ML: biCat2 ~ (continent + gender)^2 + (1 | ID) + (1 | display)

m12b.ML: biCat2 ~ (continent + gender + cAge)^2 + (1 | ID) + (1 | display)

         Df    AIC    BIC  logLik  Chisq Chi Df Pr(>Chisq)

m12b3.ML  8 5817.1 5871.9 -2900.5

m12b.ML  12 5813.4 5895.7 -2894.7 11.653      4    0.02013 *

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>

>
```

Appendix D

Ethical Application & Confirmation

UNIVERSITY OF LIVERPOOL

COMMITTEE ON RESEARCH ETHICS

APPLICATION FOR APPROVAL OF A PROJECT INVOLVING HUMAN PARTICIPANTS, HUMAN DATA, OR HUMAN MATERIAL

This application form is to be used by researchers seeking approval from the **University Committee on Research Ethics** or from an approved **School Research Ethics Committee**.

Applications to the University Research Ethics Sub-Committees, with the specified attachments, should be **submitted electronically to** ethics@liv.ac.uk. Applications to an approved School / Departmental Committee should be submitted to their local address, available at http://www.liv.ac.uk/researchethics/deptcommittees.htm.

RESEARCH MUST NOT BEGIN UNTIL ETHICAL APPROVAL HAS BEEN OBTAINED

This form must be completed by following the guidance notes, accessible at www.liv.ac.uk/researchethics.

Please complete every section, using N/A if appropriate.

Incomplete forms will be returned to the applicant.

BEFORE COMPLETING YOUR APPLICATION PLEASE CONFIRM WHAT APPROVAL YOU ARE SEEKING (please check):

a) Expedited review of an individual research project ☒
b) Full committee review of an individual research project ☐
c) Expedited generic* approval ☐
d) Committee review generic* approval ☐

*to cover a cohort of projects using similar methodologies. Boundaries of the research must be defined clearly. Approval may be granted for up to 5 years and will be subject to annual review.

***Office Use Only** (for final hard copies)*

Reference Number: RETH

Date final copy received:

Approval decision:

Approved – no conditions ☐
Committee ☐
Chairs Action ☐
Expedited ☐

Approved with conditions ☐
Committee ☐
Chairs Action ☐
Expedited ☐

Research Ethics Application Form
Version 4.1
11/1/11

1

Declaration of the:

Principal Investigator ☒ **OR** **Supervisor and Student Investigator** ☐
(please check as appropriate)

- The information in this form is accurate to the best of my knowledge and belief, and I take full responsibility for it.
- I have read and understand the University's Policy on Research Ethics
- I undertake to abide by the ethical principles underlying the Declaration of Helsinki and the University's good practice guidelines on the proper conduct of research, together with the codes of practice laid down by any relevant professional or learned society.
- If the research is approved, I undertake to adhere to the study plan, the terms of the full application of which the REC has given a favourable opinion, and any conditions set out by the REC in giving its favourable opinion.
- I undertake to seek an ethical opinion from the REC before implementing substantial amendments to the study plan or to the terms of the full application of which the REC has given a favourable opinion.
- I understand that I am responsible for monitoring the research at all times.
- If there are any serious adverse events, I understand that I am responsible for immediately stopping the research and alerting the Research Ethics Committee within 24 hours of the occurrence, via ethics@liv.ac.uk.
- I am aware of my responsibility to be up to date and comply with the requirements of the law and relevant guidelines relating to security and confidentiality of personal data.

- I understand that research records/data may be subject to inspection for audit purposes if required in future.
- I understand that personal data about me as a researcher in this application will be held by the University and that this will be managed according to the principles established in the Data Protection Act.
- I understand that the information contained in this application, any supporting documentation and all correspondence with the Research Ethics Committee relating to the application, will be subject to the provisions of the Freedom of Information Acts. The information may be disclosed in response to requests made under the Acts except where statutory exemptions apply.
- I understand that all conditions apply to any co-applicants and researchers involved in the study, and that it is my responsibility to ensure that they abide by them.
- **For Supervisors**: I understand my responsibilities as supervisor, and will ensure, to the best of my abilities, that the student investigator abides by the University's Policy on Research Ethics at all times.
- **For the Student Investigator**: I understand my responsibilities to work within a set of safety, ethical and other guidelines as agreed in advance with my supervisor and understand that I must comply with the University's regulations and any other applicable code of ethics at all times.

Signature of Principal Investigator ☒ **or** **Supervisor** ☐: ....
Date: (28/06/2012)
Print Name: Alexandra Forsythe

Signature of Student Investigator: ....
Date: (13/06/2012)

Print Name: Nichola Jones

SECTION A - IDENTIFYING INFORMATION

A1) **Title of the research** (PLEASE INCLUDE A SHORT LAY TITLE IN BRACKETS).

Understanding Beauty- Fractal Dimension and Preference

A2) **Principal Investigator** ☐ **OR** **Supervisor** ☒ **(please check as appropriate)**

Title:	Dr.	**Staff number:**	451428
Forename/Initials:	Alex	**Surname:**	Forsythe
Post:		**Department:**	Psychology
Telephone:	0151 794 3912	**E-mail:**	amf@liverpool.ac.uk

A3) **Co-applicants (including student investigators)**

Title and Name	Post / Current programme (if student investigator)	Department/ School/Institution if not UoL	Phone	Email
Miss Nichola Jones	PhD student	School of Psychology	07765711424	nichola.jones@liv.ac.uk

SECTION B - PROJECT DETAILS

B1) **Proposed study dates and duration** (RESEARCH **MUST NOT BEGIN** UNTIL ETHICAL APPROVAL HAS BEEN OBTAINED)

Please complete as appropriate:

EITHER

a) Starting as soon as ethical approval has been obtained ☒ **(please check if applicable)**

Approximate end date:	October 2012

OR

b) Approximate dates:

Start date:		**End date:**	

B2) **Give a full lay summary of the purpose, design and methodology of the planned research.**

This project aims to explore processing level factors that influence our experiences of beauty and aesthetic pleasure; we hope to develop an established measure of visual beauty (based on complexity and fractal dimension) and further extend this work through an analysis of cultural and developmental aspects of the perception of beauty in art and nature through fractal analyses.

The aim of this project is to explore two interlinked ideas, (i) that there exists an optimum range of fractal dimension, that this range is closely linked with experiences of aesthetic pleasure and that (ii) this preference range is truly universal across age, developmental environments and culture.

The project uses the family of shapes called 'fractals' as a quantitative measure of complex patterns and processes in nature and art. Fractals are shapes that demonstrate self-similarity at varying scales and can be found commonly in nature as well as art, each part of a fractal image is statistically similar to the whole at different magnified scales, these patterns can be seen across various natural occurrences, (e.g. mountains, clouds & coastlines) and have also been found within the human body.

Fractal patterns and their link to natures beautiful scenes means that the links between Fractal Dimension (FD) and aesthetic preference are well established (Spehar et al 2003; Taylor et al, 2005b). It has also been suggested that fractals tap into specialist cognitive modules that have developed to moderate information about living things (Wilson, 1984) and that such modules are linked with emotional regulation and reduction of physiological stress (Taylor, 1999)

Studies have found that there seems to be a universal preference for mid-range fractals, regardless of the format the fractal is displayed in, whether they show natural scenes, computer generated patterns or artistically generated fractals (Forsythe et al., 2011; Taylor & Sprott, 2008). Although well supported, this research however fails to offer definitive rationale of why we appear to prefer images displaying mid-range fractal patterns over those that are not fractal or that fall outside of this range. The research also fails to offer a fully representative sample in its participants, with much research being based on Western educated undergraduate psychology students (the WEIRD population), this is a rising problem within the field pf psychology and

perception (Henrich et al, 2010) especially when making assertions about universal of human experience.

Fractal analysis has extsablished its usefulness in understanding the degeneration of artworks by artists susquently diagnosed with neurological deterioration (Williams & Forsythe, 2009) as well as determining the authenticity of artwork, such as Jackson Pollock's (Taylor, 2002). Recent research has attempted to explain the link between aesthetic preference and fractal images in further detail building on the physiological links in fractal dynamical research. In one such attempt Taylor et al (2011) found that the scan paths the eye takes when in search mode are fractal. The research suggests that the eye adopts a FD of mid-range between 1.3 and 1.5 in any situation, regardless of the visual stimulus. There's good reason for the eye to adopt a trajectory pattern that is within the mid range of FD around 1.5, this is because it the optimal path for the eye to cover space most efficiently, the link between this and aesthetic expereince raise more questions reagrding the reasoning behind this.
The connection between mid-range fractals and nature has be suggested to offer closer understanding as to why we prefer D values between 1.3-1.5, Aks & Sprott (1996) suggest that people's preference is universally set at 1.3 because of continual visual exposure to nature's patterns, Rogowitz & Voss (1990) also suggest evolutionary exposure foundation for mid-preference, because for millions of years, humans have been exposed to nature's fractals and during this time our visual system has evolved to recognise them with ease. More recent evidence, however would suggest that there is significant variation in the D values found in nature offering criticism to previous theories. Clouds do indeed exhibit 1.3 D values (Lovejoy, 1982) as do waves (Werner, 1999) however coastlines have much more variety with evidence suggesting a range between 1.05-1.52 (Mandelbrot, 1982, Feder, 1988) and the distribution of stars in the scale demonstrate much lower D values (Mandelbrot, 1982).
The environment we spend the most time in today is significantly different to the natural world in which we evolved, the world is filled with Euclidean shapes in buildings, roads and computer screen and even if we can see nature, however we need further testing to understand the role that exposure plays in understanding preference in fractal scenes.

As we can see from previous research, it seems like mid-range fractals elicit some exciting perceptual responses, most of which are not yet fully explained and need further investigation.

Previous pilot data carried out for this thesis found interesting but incomplete data from an international sample. The research used the same survey, but was distributed using MTurk participant sampling tool. This method yeilded a large set of results (N=281), from 30 countries, despite the size of the sample, the distribution of samples was skewed by population of 192 (68.1%) Indian participants. In the present study we hope to gather data that can be used in conjunction with previous findings to offer a fuller picture of the preference of fractal images across geographic location as well as other variables.

The research questions explore if mid-range fractal dimension in a scene act as determinants of beauty or are cultural and developmental factors more salient?
1- Culturally & developmentally Variant Question: Will participants prefer images/scenes with a FD similar to the environment in which they developed, and is this preference subject to change throughout life time?
2- Culturally and developmentally Invariant Question: Will participants of all cultures and ages surveyed within this project preference FD images/scenes which are closest to the Taylor et al, mid-range (1.3-1.5D) dimension?

Methodology & Analysis:

To test these we will use a short online and/or printed survey design (lasting approx 15 minutes) this method was chosen to ensure maximum participants the online version providing a cost and time-effective way of getting a large sample size and the hard copy version offering a method for data collection with participants that do not have access to computer or lack confidence to complete the survey online.
In the study participants will be shown a series of paired images. The image used will be computer generated fractal patterns, these images are abstract black and white complex shapes developed specifically for this study by Prof. Richard Taylor (University of Oreagon). In all pair sets the participant will be asked to select (with a click on the screen or a tick over the image) 1 image from the pair that they "like best". A forced choice design was used as the stimuli are not overtly beautiful therefore likert scale data collection would be unsuitable. The sample will aim to collect data from as many geographic locations and age samples as possible.

This project aims to use 3 distinct groups for data collection, all of which will take part in identical studies so that comparisons can be made across samples. The samples hope to gain a deeper understanding into 2 factors, firstly re-testing the established mid-range preference hypothesis (Taylor et al 2011) and secondly offering insight into the grounding of fractal preference- looking at developmental and environmental factors and their influence on expereinces of beauty. The group being examined are explained below:

a) large UK sample population:This sample it is predicted will include a large number of University of Liverpool undergraduate students, as well as a larger UK sample than previously attained (in pilot work). Since the aim of this is to obtain the bigest sample possible, the survey link will also take advantage of the population on social networking sites, incluidng twitter and facebook as well as more specialised participant sampling systems.

b) Elderly Population: As part of understanding the developmental factors that may infleunce of fractal perception, it is hoped that we can gained a sample that can show if mid-range preference is consistent throughout a life-span.

c) International population: Participants will be recruited via online advertisement (on social media/networking sites) and also from within international Universities (distributed via email) to enable a more universal view of preference to be formed.

B3) **List any research assistants, sub-contractors or other staff not named above who will be involved in the research and detail their involvement.**

N/A

B4) **List below all research sites, and their Lead Investigators, to be included in this study.**

Research Site	Individual Responsible	Position and contact details

B5) **Are the results of the study to be disseminated in the public domain?**

YES ☒ NO ☐

➢ ***If not, why not?***

N/A

B6) **Give details of the funding of the research, including funding organisation(s), amount applied for or secured, duration, and UOL reference**

Funding Body	Amount	Duration	UoL Reference

B7) **Give details of any interests, commercial or otherwise, you or your co-applicants have in the funding body.**

N/A

SECTION C - EXPEDITED REVIEW

C1)

a) Will the study involve recruitment of participants outside the UK?	Yes
b) Does the study involve participants who are particularly vulnerable or unable to give informed consent? *(e.g. children, people with learning or communication disabilities, people in custody, people engaged in illegal activities such as drug-taking, your own students in an educational capacity) (Note: this does not include secondary data authorised for release by the data collector for research purposes.)*	No
c) Will the study require obtaining consent from a "research participant advocate" (for definition see guidance notes) in lieu of participants who are unable to give informed consent? *(e.g. for research involving children or, people with learning or communication disabilities)*	No

with learning or communication disabilities)	
d) Will it be necessary for participants, whose consent to participate in the study will be required, to take part without their knowledge at the time? *(e.g. covert observation using photography or video recording)*	No
e) Does the study involve deliberately misleading the participants?	No
f) Will the study require discussion of sensitive topics that may cause distress or embarrassment to the participant or potential risk of disclosure to the researcher of criminal activity or child protection issues? *(e.g. sexual activity, criminal activity)*	No
g) Are drugs, placebos or other substances (e.g. food substances, vitamins) to be administered to the study participants or will the study involve invasive, intrusive or potentially harmful procedures of any kind?	No
h) Will samples (e.g. blood, DNA, tissue) be obtained from participants?	No
i) Is pain or more than mild discomfort likely to result from the study?	No

j) Could the study induce psychological stress or anxiety or cause harm or negative consequences beyond the risks encountered in normal life?	No
k) Will the study involve prolonged or repetitive testing?	No
l) Will financial inducements (other than reasonable expenses and compensation for time) be offered to participants?	No

C2)

a) Will the study seek written, informed consent?	No
b) Will participants be informed that their participation is voluntary?	Yes
c) Will participants be informed that they are free to withdraw at any time?	Yes
d) Will participants be informed of aspects relevant to their continued participation in the study?	Yes
e) Will participants' data remain confidential?	Yes
f) Will participants be debriefed?	Yes

If you have answered 'no' to all items in SECTION C1 and 'yes' to all questions in SECTION C2 the application will be processed through expedited review.

If you have answered "Yes" to one or more questions in Section C1, or "No" to one or more questions in Section C2, but wish to apply for expedited review, please make the case below. See research ethics website for an example "case for expedited review".

C3) **Case for Expedited Review** – *To be used if asking for expedited review despite answering YES to questions in C1 or NO to answers in C2.*

C2 a) Will the study seek written, informed consent? No

The research uses an online-survey design, therefore the problems arising from obtaining informed consent are not regarded. Participants will be required to answer a full set of quesiton demonstrating there understanding of the task and acting as signed informed consent equivilent, participants will also be as debreifed as much as possible, and left with a contact email and number should they wish to conatact the researcher directly with concerns or questions.

C1 a) Will the study involve recruitment of participants outside the UK? Yes

The recruitment will be done online- therefore it is likely that using the chain referral sampling system participants will be recruited from outside the UK.. Pilot studies using Mturk for international samples for this research has previosuly obtained ethical approval from Aberyswyth University- the institution at which I was previously studying. The call for more data involving international participants is based upon some interesting results found at the piloting stage, results that require further investigation with larger samples from different countries needed to comparison analysis. Dependant on the amount of participant recruited using this method, participants will also be recruited from Universities across the world, primarily psychology departments- this population was chosen as the participants will be familiar with the nature of being involved with research and the daily use of computers- meaning the influence of the online-survey will be minimal to there everyday life, they will also, it is hoped recongise the need to take part in research therefore producing the highest participants possible.

SECTION D - PARTICIPANT DETAILS

D1) **How many participants will be recruited?**

100+

D2) **How was the number of participants decided upon?**

This is viewed as an attainable scale for an online survey design.

D3)

a) **Describe how potential participants in the study will be identified, approached and recruited.**

Recruitment will use both opportunity and chain referral sampling to distribute the survey to as wide a population as possible. 'Call for volunteer' ads will be placed on social networking sites (twitter and facebook) as well as more specific participant sampling pool websites (PSY-PAG forum & Uni of Liverpool News Feed) and participants will be asked to distribute the survey to as many people they wish.
More targetted samples will be used for overseas participants, this will include sending emails/letters (written in English only) directly to departments (mainly psychology) and asking them to distribute the survey through staff and students or anyone who would be interested in participating in the research.

b) **Inclusion criteria:**

Good visual capacity (including participant who wear glasses or contacts as long participant were corrective material during testing) Ability to understand written english 18+yrs Willingness to take part

c) **Exclusion criteria:**

Participants under 18 will be excluded.

d) **Are any specific groups to be excluded from this study? If so please list them and explain why:**

N/A

e) **Give details for cases and controls separately if appropriate:**

N/A

f) **Give details of any advertisements:**

A simple advert will be used asking people to take part in a short online survey in which they will view a set of images and indicate preference. If participants are interested they will be provided with the link to the survey, which also gives further details of the involvement required in the study.

D4)

a) **State the numbers of participants from any of the following vulnerable groups and justify their inclusion**

Children under 16 years of age:	-
Adults with learning disabilities:	-
Adults with dementia:	-
Prisoners:	-
Young Offenders:	-
Adults who are unable to consent for themselves:	-
Those who could be considered to have a particularly dependent relationship with the investigator, e.g. those in care homes, students of the PI or Co-applicants:	-
Other vulnerable groups (please list):	-

b) **State the numbers of healthy volunteer participants:**

Healthy Volunteers	**100+**

D5)

a) **Describe the arrangements for gaining informed consent from the research participants.**

Online Survey: The participants will initially be directed to an information page telling them about the study, after this the participants are taken to a page to act as confirmation of informed consent to continue with the study. Informed consent will be collected using a series of questions that confirm their willingness to take part, full understanding of what will happen and reassurance of their rights to withdraw at any point without explanation. After this participants will be asked for some information, including date of birth and gender. Participants will also be asked to provide information about their place of birth, and the country in which they spent the majority of there childhood, Furthermore participants will be asked to indicate if they grew up in an urban or rural environment. They will also be asked for a name/pseudonym that they wish to be called by, this is collected should the participant wish to withdraw their data from the study after collection has finished. Participants will be made aware that they can do this until 2 weeks after testing, when data will be merged into a master file, making personal recognition not possible. Participants after giving these details will be directed through a series of paired image, they will be asked to select the image they like best from every pair displayed. After giving preference ratings for the images participants will be directed to a de-brief page.

Hard Copy Survey:Participants will be asked to read the information sheet after expressing an interest in taking part in the survey, after this if they still wish to continue they will be asked to read and sign a consent form confirming their willingness to take part, full understanding of what will happen and reassurance of their rights to withdraw at any point without explanation. Participants will then be asked to fill out some information including DOB, location and a anonymous participant code will be provided to them to keep. Participants will be made aware that if they wish to remove there results from the study they shoudl use this participant code, they can do this until 2 weeks after testing, when data will be merged into a master file, making personal recognition not possible. Participants after giving these details will be asked to look through a series of printed paired images, they will be asked to select the image they like best from every pair displayed. After giving preferences for the images participants will be given a de-brief sheet to further explain the purposes of the study and that contains contact details for the senior researcher should they wish to discuss anything after the study has finished.

b) **If participants are to be recruited from any of the potentially vulnerable groups listed above, give details of extra steps taken to assure their protection, including arrangements to obtain consent from a legal, political or other appropriate representative in addition to the consent of the participant** *(e.g. HM Prison Service for research with young offenders, Head Teachers for research with children etc.).*

N/A

c) **If participants might not adequately understand verbal explanations or written information given in English, describe the arrangements for those participants (e.g. translation, use of interpreters etc.)**

Only participants with full ability to read English will be recruited as no traslation will be used.

d) **Where informed consent is not to be obtained (including the deception of participants) please explain why.**

N/A

D6) What is the potential for benefit to research participants, if any?

Hoped that the participants will enjoy talking part in the study- active involvement with research. No other benefits.

D7) State any fees, reimbursements for time and inconvenience, or other forms of compensation that individual research participants may receive. Include direct payments, reimbursement of expenses or any other benefits of taking part in the research?

N/A

SECTION E - RISKS AND THEIR MANAGEMENT

E1) Describe in detail the potential physical or psychological adverse effects, risks or hazards (minimal, moderate, high or severe) of involvement in the research for research participants.

There are no foreseen potential risks to the participant, either physical or psychological; participants will be able to end the study at any time if they feel they do not wish to continue without having to give reason, this will be made clear prior to testing to avoid any external pressure the participant may feel to continue if feeling uncomfortable.

E2) Explain how the potential benefits of the research outweigh any risks to the participants.

No potential risks to participants whilst taking part in the study.

E3) **Describe in detail the potential adverse effects, risks or hazards (minimal, moderate, high or severe) of involvement in the research for the researchers.**

There are no potential risks to the interests of the researcher foreseen within this project.

E4) **Will individual or group interviews/questionnaires discuss any topics or issues that might be sensitive, embarrassing or upsetting, or is it possible that criminal or other disclosures requiring action could take place during the study (e.g. during interviews/group discussions, or use of screening tests for drugs)?**

YES ☐ NO ☒

➢ ***If Yes, give details of procedures in place to deal with these issues.***

N/A

E5) **Describe the measures in place in the event of any unexpected outcomes or adverse events to participants arising from their involvement in the project**

The stimulus images are monochromatic abstract shapes that have no obvious semantic meaning- therefore it is not expected that participants will experience adverse outcomes from

taking part in the research, however should a case appear, participants during de-brief will have access to the contact details of the main researcher and the senior researcher if they wish to discuss the study in further detail to address a problem or make a complaint.

E6) **Explain how the conduct of the project will be monitored to ensure that it conforms with the study plan and relevant University policies and guidance.**

The survey is a stringent design and participants cannot stray from the study plan if they wish to complete the survey fully.

SECTION F - DATA ACCESS AND STORAGE

F1) **Where the research involves any of the following activities at any stage (including identification of potential research participants), state what measures have been put in place to ensure confidentiality of personal data (e.g. encryption or other anonymisation procedures will be used)**

Electronic transfer of data by magnetic or optical media, e-mail or computer networks	The survey distributor, surveygizmo.co.uk have secure servers and once the data has been exported from the website it will be permanently deleted from the site.
Sharing of data with other organisations	-
Export of data outside the European Union	-

Use of personal addresses, postcodes, faxes, e-mails or telephone numbers	Only names/pseudonyms will be requested from each participants (in order to indentify participants should they wish to withdraw their data upto 2weeks after collection), these will be deleted securely once the master file containing all the participants information has been compiled.
Publication of direct quotations from respondents	N/A
Publication of data that might allow identification of individuals	Participants will not be identifiable from the data published as all recognisable information will be removed prior to analysis.
Use of audio/visual recording devices	N/A
Storage of personal data on any of the following:	All data will be secured on a portable storage device and secured using a password(also backed up and password secured on another device). This device will be stored in a safe place, a locked office or room, when it is not being used. All information will be stored on this and not saved to any laptops or computers whether they be private or public use.
Manual files	All hard files will be stored in a locked filing cabinet within a secure office space, only the main researcher and members of the supervisory team will have access to these documents.
Home or other personal computers	Only a data storage device will be used to view the data and never saved onto the device.
University computers	Only a data storage device will be used to view the data and never saved onto the device.
Private company computers	Only a data storage device will be used to view the data and never saved onto the device.
Laptop computers	Only a data storage device will be used to view the data and never saved onto the device.

F2) Who will have control of and act as the custodian for the data generated by the study?

The main researchers (myself) and the senior researcher and superviosory team (Dr. A Forsythe & Dr. M Bertamini)

F3) Who will have access to the data generated by the study?

Only the immediate research group with have access to the data, this includes myself (the primary researcher) and both of my supervisors, Dr. Alex Forysthe and Dr. Marco Bertamini

F4) For how long will data from the study be stored?

Data will be until the end of my PhD, within 2years it will be erased securely and permanently.

SECTION G – PEER REVIEW

G1)

a) Has the project undergone peer review?

YES ☒ NO ☐

b) If yes, by whom was this carried out? *(please enclose evidence if available)*

Project has undergone consistent peer review as the work is towards a PhD thesis. The intitial review included the acceptance of the research proposal and continual review is gained from lab meeting presentations and supervisory meetings.

SECTION G - CHECKLIST OF ENCLOSURES

Study Plan / Protocol	Yes
Recruitment advertisement	Yes

Participant information sheet	Yes
Participant Consent form	Yes
Research Participant Advocate Consent form	N/A
Evidence of external approvals	N/A
Questionnaires on sensitive topics	N/A
Interview schedule	N/A
Debriefing material	Yes
Other (please specify)	N/A
Evidence of peer review (If G1 = Yes)	N/A

Dear Alex

Your Ethics Application has been approved (with no need for changes) by the Institute of Psychology, Health and Society's Ethics Committee:

Reference: PSYC-1112-104

Principal Investigator: Alex Forsythe

Project Title: Understanding Beauty - Fractal Dimension and Preference

First Reviewer: Ben Ambridge

Second Reviewer: Ian Schermbrucker

As the principal investigator (PI), it is your responsibility to keep the final, approved version of your Ethics Application form for this project and to provide it to any students or other collaborators who also work on this project *before* they begin work on the project.

All undergraduate and taught masters students will need to bind a hard copy of this Ethics Application approval email *and* a copy of your final, approved Ethics Application form into any work that they submit based on this project (e.g., third year projects and Master's dissertation projects). They will also need to bind into their work hard copies of any participant information sheets, consent forms, and debriefing forms used during the project.

Yours sincerely

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