Aesthetic Appreciation Explicated
Östen Axelsson
Abstract

The present doctoral thesis outlines a new model in psychological aesthetics, named the Information-Load Model. This model asserts that aesthetic appreciation is grounded in the relationship between the amount of information of stimuli and people’s capacity to process this information. This relationship results in information load, which in turn creates emotional responses to stimuli. Aesthetic appreciation corresponds to an optimal degree of information load. Initially, the optimal degree is relatively low. As an individual learns to master information in a domain (e.g., photography), the degree of information load, which corresponds to aesthetic appreciation, increases.

The present doctoral thesis is based on three empirical papers that explored what factors determine aesthetic appreciation of photographs and soundscapes. Experiment 1 of Paper I involved 34 psychology undergraduates and 564 photographs of various motifs. It resulted in a set of 189 adjectives related to the degree of aesthetic appreciation of photographs. The subsequent experiments employed attribute scales that were derived from this set of adjectives. In Experiment 2 of Paper I, 100 university students scaled 50 photographs on 141 attribute scales. Similarly, in Paper II, 100 university students scaled 50 soundscapes on 116 attribute scales. In Paper III, 10 psychology undergraduates and 5 photo professionals scaled 32 photographs on 27 attribute scales. To explore the underlying structure of the data sets, they were subjected to Multidimensional Scaling and Principal Components Analyses. Four general components, related to aesthetic appreciation, were found: Familiarity, Hedonic Tone, Expressiveness, and Uncertainty. These components result from the higher-order latent factor Information Load that underlies aesthetic appreciation.

Keywords: Aesthetic Appreciation, Information-Load Model, Photographs, Soundscapes, Theory Development.
List of Papers

The present doctoral thesis is based on the following three papers, which will be referred to in the text with their Roman numerals.


The papers are reproduced with permission of the publishers:

¹ Copyright © 2007, Perceptual and Motor Skills
² Copyright © 2010, Acoustical Society of America
³ Copyright © 2007, American Psychological Association
## Contents

1. We Need a Solid Theoretic Framework ........................................ 1
   1.1. Aesthetics concerns the sensuous ..................................... 1
   1.2. What factors determine aesthetic appreciation? ...................... 2

2. Five Central Models of Aesthetic Appreciation ............................. 5
   2.1. Berlyne's Collative-Motivational Model .............................. 5
   2.2. The Preference-for-Prototypes Model .................................. 8
   2.3. The Preference-for-Fluency Model ..................................... 10
   2.4. Silvia's Appraisal-of-Interest Model .................................. 11
   2.5. Eckblad's Cognitive-Motivational Model ............................... 11

3. Aesthetic Appreciation is Grounded in Information Processing .......... 15

4. My Empirical Results Support Integration of Previous Models .......... 19
   4.1. I aim to develop a new model of aesthetic appreciation .......... 19
       4.1.1. Towards a psychology of photography (Paper I) ............ 19
       4.1.2. A principal components model of soundscape perception (Paper II) .............................................. 20
       4.1.3. Individual differences in preferences to photographs (Paper III) ................................................. 21
   4.2. Future models in psychological aesthetics must handle individual differences ................................................... 23

5. Towards an Information-Load Model ........................................... 25
   5.1. The Information-Load Model as a vector representation .......... 26
   5.2. A model for measuring degree of information load ................ 27
   5.3. The Information-Load Model in relation to previous models ...... 29

6. Information Load is the Key Factor Underlying Aesthetic Appreciation ................................................................................. 31
   6.1. People can verbalise degree of information load .................... 32
   6.2. Attributes related to aesthetic appreciation are ordered along the information-load dimension ............................................ 33
   6.3. A gap in the principal-component solution indicates Information Load ................................................................. 38
   6.4. Information Load represents something real .......................... 40
   6.5. Information Load is independent of methods .......................... 42

7. Information Load is a Fruitful Concept ....................................... 45
   7.1. Information Load is not an artefact ..................................... 45
   7.2. Aesthetic appreciation is properly measured and mapped ...... 45
1. We Need a Solid Theoretic Framework

Whether to advance the research on aesthetic appreciation or to create compound aesthetic entities, it is essential to hold a theoretic framework to guide the quest. Without a framework we grope in the dark and are at the mercy of our own unrestrained imagination. The creative mind may welcome this liberty, but unguided it is likely to lose its objectives, like an actor without director or an orchestra without conductor.

The scientist needs direction on how to select stimuli, on how to design measuring instruments and studies, on what data collection procedures to use, and on how to interpret the results. Without a theoretic context, research is meaningless. To creatives, an aesthetics framework provides guidance for how to achieve desired impacts, regardless if to trouble or to please. So far, psychological aesthetics is unable to provide this firm support. A handful of scientists have endeavoured to create models and tentative theories. Nevertheless, all established models seem to fall short in one way or another.

1.1. Aesthetics concerns the sensuous

Surely, the sensuous has fascinated human beings since before the dawn of cultural expressions, such as art. However, it was not until the 18th century, when the revolution and emancipation of the natural sciences made it clear that art and science—or beauty and truth—are separate, that a systematic investigation into the nature of the sensuous began in Europe (Kristeller, 1998). It was at this time the German philosopher Alexander Baumgarten (1954/1735) coined the term ‘aesthetics’ to denote the science of the sensuous faculty of knowledge. Baumgarten derived the term from the Greek word for sensory perception, aesthesis. Ever since, philosophers have competed to outperform each other in defining this elusive concept. Despite 300 years of debate there is no consensus on a definition.

In the late 19th century, when academic psychology had just experienced its dawn, Gustav Theodor Fechner (1876) pioneered psychological aesthetics when he approached the nature of the sensuous by experimental observations. In particular, he was interested in aesthetic appreciation of pleasant forms, like the Golden Section. The notion that mathematic proportions should correspond to aesthetic appreciation fascinated him (Boring, 1950; Höge, 1995).

Fechner was also the first to use empirical methods to investigate aesthetic appreciation to works of art. When the Dresden museum exhibited the two versions of Holbein’s Madonna in 1871, Fechner left his study to enquire
museum visitors about their judgments on these two paintings. From this time on, the development of psychological aesthetics would be grounded in academic psychology.

1.2. What factors determine aesthetic appreciation?
The present doctoral thesis is based on three empirical studies in which I explored what factors determine aesthetic appreciation (Papers I–III). In line with current practice in psychological aesthetics, and inspired by James A. Russell’s pioneering work in environmental psychology, as well as, his research on emotion (e.g., Mehrabian & Russell, 1974; Russell, 1980, 2003), I focus particularly on the perceived affective and conceptual qualities of stimuli (Table 1). Affective quality is a property of the stimulus, referring to its capacity to change our emotional responses (Russell, 2003). For example, I may feel comfortable in an environment and express that the environment is pleasant. Thus, ‘pleasantness’ is a perceived affective quality, because it derives from the stimulus and is not a property of the perceiver. Similarly, ‘conceptual quality’ refers to the meaning of the stimulus. For example, a stimulus may be hard to classify and is perceived as unfamiliar, complex or ambiguous.

Because of the lack of consensus in regard to how ‘aesthetics’ or ‘aesthetic appreciation’ should be defined—besides the general agreement that aesthetics concerns the sensuous—I follow the current practise in psychological aesthetics and use operational definitions. In Paper I, I used an aesthetic-appeal scale as dependent variable. In Paper III, I followed the current practice and used a preference scale. In addition, I included attribute scales measuring affective qualities like ‘Aesthetic’ and ‘Appealing’ in all three studies. Typically, all these scales have high coefficients of correlations and load in the same component derived from a Principal Components Analysis (Papers I–III).

Only factors that contribute to aesthetic appreciation fall within the scope of the present doctoral thesis. Psychological aesthetics is a sub-domain of the psychology of emotions and evaluation. Although psychological research on emotions, evaluation and aesthetics fertilise each other and partially overlap, psychological research on aesthetic appreciation does principally not answer questions on emotions and evaluation beyond aesthetics.

Table 1. Terms and definitions used in the present doctoral thesis.

<table>
<thead>
<tr>
<th>Term</th>
<th>Definition and explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Affective quality</td>
<td>Property of the stimulus, referring to its capacity to change our emotional responses (e.g., pleasant).</td>
</tr>
<tr>
<td>Conceptual quality</td>
<td>Property of the stimulus, referring to its meaning and how easy or hard it is to categorise or recognise (e.g., ambiguous).</td>
</tr>
<tr>
<td>Amount of information</td>
<td>Perceptual or conceptual complexity of stimuli, or occurrence of unexpected events, in the same way as Claude Shannon defined information as occurrence of the improbable (cf. entropy).</td>
</tr>
<tr>
<td>Information processing capacity</td>
<td>Capacity to deal with uncertainty and to comprehend stimuli, in a particular domain (e.g., photography), as a result of experience or practice in that domain.</td>
</tr>
<tr>
<td>Information load</td>
<td>Demand on the individual’s cognitive-affective resources. Information processing results in some degree of resistance, called information load, which increases with the amount of information of stimuli, and decreases with information processing capacity.</td>
</tr>
</tbody>
</table>
2. Five Central Models of Aesthetic Appreciation

This chapter presents five theoretic models that are central to the development of psychological aesthetics: (1) Berlyne’s Collative-Motivational Model, (2) the Preference-for-Prototypes Model, (3) the Preference-for-Fluency Model, (4) Silvia’s Appraisal-of-Interest Model, and (5) Eckblad’s Cognitive-Motivational Model. I regard the Preference-for-Fluency Model as an extension of the Preference-for-Prototypes Model. Therefore, after this introductory chapter of the present doctoral thesis, I will treat these two models as more or less equivalent. The Preference-for-Prototypes Model is currently the most applied model in psychological aesthetics.

There are other models proposed in psychological aesthetics, like Leder et al.’s (2004) model of aesthetic appreciation and aesthetic judgments. Nevertheless, the five included models are the most important to the present doctoral thesis.

2.1. Berlyne’s Collative-Motivational Model

The hitherto most influential model in psychological aesthetics is Berlyne’s Collative-Motivational Model that evolved between 1950 and 1971, during which period behaviourist thoughts dominated academic psychology. Although this model is old, it is still central to the theoretic discussion in psychological aesthetics and is debated repeatedly (e.g., North & Hargreaves, 2000; Whitfield, 2000; Silvia, 2006b). It serves as the main background and point of departure in the development of all subsequent, central models in psychological aesthetics.

Berlyne (1967, 1971) built his Collative-Motivational Model on the two general concepts ‘Hedonic Tone’ and ‘Arousal’, and the well-established fact that organisms prefer a moderate level of overall arousal, whereas both high and low levels of arousal are unpleasant (cf. the Yerkes-Dodson law; Yerkes & Dodson, 1908). Hedonic Tone is related to reward or positive reinforcement, which were two central concepts in the behaviourist theories of learning (e.g., Hull, 1943; Skinner, 1953). These theories were influential during the period Berlyne developed his model (Berlyne, 1950, 1960, 1967, 1971). Arousal, on the other hand, has been important in psychology since James (1884) and Lange (1912/1885) independently proposed that emotions depend on physical responses to specific arousing situations. However, it was not until Moruzzi
and Magoun (1949) described the activating function of the reticular formation and related brain structures that widespread interest in the concept of arousal begun. Arousal soon became one of the most central concepts in psychology and motivation research, particularly associated with the directive aspects of emotional or motivational processes (cf. Duffy, 1934, 1957, 1966).

According to Berlyne (1960, 1967, 1971), all stimuli have the potential to evoke arousal. The ‘arousal potential’ of stimuli depends on three major classes of stimulus properties. First, the psychophysical properties are associated with the intensity of the stimuli, for example, brightness, loudness, and saturation. The more intense the psychophysical properties are the more arousing. Second, the ecological properties are associated with biological noxious or beneficial conditions, for example, pain and perceived threat. Lastly, the collative properties concern collating incoming perceptual inputs with existing information, and reflect a degree of discrepancy between these two sources: Novelty, often accompanied by surprise and incongruity, reflects conflict between present stimulus, and past experiences and expectations. Complexity refers to the amount of variety or diversity among elements in a stimulus pattern. Uncertainty is conflict resulting from simultaneously aroused, incompatible expectations implied by incomplete and thus ambiguous information. Conflict refers to the simultaneous presence of incompatible, nearly equally strong possibilities (Berlyne, 1960). Please observe that ‘arousal potential’ refers to properties of stimuli and not to the effect stimuli has on the arousal system. Furthermore, among the three property classes (psychophysical, ecological and collative), Berlyne considered the collative properties to be the most important to aesthetics.

Berlyne (1967, 1971) proposed that the hedonic tone of stimuli is a curvilinear function of their arousal potential. This was an extension of Wundt’s (1874) findings that the pleasantness or unpleasantness of stimuli followed an inverted U-shaped function of their intensity, that is, of the psychophysical properties of stimuli. Thus, Berlyne extended these results to encompass also the ecological and collative properties. This addition is possibly Berlyne’s most important contribution to the theoretical development of psychological aesthetics.

In order to create a framework for his model, Berlyne (1971) turned to neuroscience and James and Marianne Olds research on brain-stimulation reward. Berlyne proposed that there are three interrelated neural systems of importance. He named these: (1) ‘the primary reward system’, (2) ‘the aversion system’, and (3) ‘the secondary reward system’, and suggested that these three systems correspond to the lateral hypothalamic-medial forebrain bundle, the medial hypothalamus projections onto the tectal system, and the limbic system, respectively.

James and Marianne Olds had shown that these three neural systems are related to reward and punishment, and are inhibitory interconnected (Olds & Olds, 1965). The limbic system (secondary reward system) inhibits activity in the tectal system (aversion system), which in turn inhibits activity in the medial forebrain bundle (primary reward system). Berlyne (1971) hypothesised further that arousal potential of stimuli activates these systems, and in such a way that the primary reward system is activated prior to the aversion system, which is activated prior to the secondary reward system.

Moreover, Berlyne (1971) proposed that there are two mechanisms of positive hedonic tone. First, extremely high arousal is unpleasant. Therefore, when arousal approaches the upper extreme, a decrease to a lower arousal level is pleasurable and rewarding. Second, a limited rise in arousal, which is not enough to drive arousal up to the unpleasant range, can be pleasant.

Berlyne suggested that the first mechanism depends on the secondary reward system, which reduces the activity of the aversion system. Once the aversion system is inhibited the primary reward system will be disinhibited, which will lead to pleasure and reward. On the other hand, when reward comes from moderate arousal increase, and has nothing to do with arousal reduction,
the primary reward system will be excited directly and the other two systems are not necessary.

In order to explain the proposed inverted U-shaped function between arousal potential of stimuli and Hedonic Tone, Berlyne (1967, 1971) assumed that all neurons, of both the primary reward system and the aversion system, will have their individual thresholds, and that these thresholds differ according to a normal distribution. Moreover, Berlyne assumed that the average threshold for neurons in the aversion system is higher than the average threshold for neurons in the primary reward system. This means that it will take more arousal potential to activate the aversion system than the primary reward system. These assumptions are illustrated in the upper panel of Figure 1 that shows the proposed normal distribution of the number of neurons in the two neural systems that are activated by a certain degree of arousal potential. Finally, to create the inverted U-shaped function Berlyne had to make two more assumptions: (1) that at any given moment after being activated, the aversion system has more activated neurons than the primary reward system, and (2) that the hedonic tone of stimuli is the net sum effect of the activation of the primary reward system minus the activation of the aversion system. The latter is illustrated in the lower panel of Figure 1 that shows the accumulated activity in the two neural systems, as well as, the resulting Hedonic Tone function.

Current research in ‘neuroaesthetics’ still finds an interest in the reward systems of the brain, including mesolimbic structures, like the nucleus accumbens and the ventral tegmental area, as well as, the hypothalamus and insula. These areas are thought to be involved in regulating autonomic and physiological responses to rewarding and emotional stimuli. In addition, there is a focus on cortical areas associated with cognitive functions, such as, recording rewarding stimuli and emotional control, for example, orbito frontal and inferior frontal cortex (e.g., Menon & Levetin, 2005). However, we still do not know how these areas are related to aesthetic appreciation (e.g., Cinzia & Vittorio, 2009; Levetin & Tirovolas, 2009).

2.2. The Preference-for-Prototypes Model

In the 1970s researchers discovered that the inverted U-shaped Hedonic Tone-Arousal Potential function had low predictive ability in the case of familiar, natural object categories, such as, representational paintings (Berlyne, 1975; O’Hare, 1976; O’Hare & Gordon, 1977), buildings (Gärling, 1976), and furniture (Whitfield & Slatter, 1979). These findings suggested that the category an item belong to play an important role in aesthetic appreciation.

Traditionally category membership has been treated as a digital, all-or-none phenomenon. Behind this view lies an assumption that categories are logical bounded entities in which membership is defined by an item’s possession of a set of criterial features. In this view, all members of a category are believed to have a full and equal degree of membership. In her extensive investigation of human categorisation, Rosch (e.g., 1975; Rosch & Mervis, 1975) showed that natural categories are structured in analogue rather than digital fashion. She argued that the human mind process natural categories in terms of their internal structure; Categories are represented in cognition in terms of a prototype (the clearest cases, best examples) of the category, with non-prototype members tending towards an order from better to poorer examples, decreasing in similarity to the prototype and of decreasing degree of membership.

These results led Whitfield (1983) to propose the Preference-for-Prototypes Model. This model advocates that preference for category members is a positive and monotonic function of their prototypicality (see also Whitfield & Slatter, 1979). Thus, the more typical, familiar or meaningful a category member is, the more it is preferred.

For example, prototypicality effects have been shown for furniture (Whitfield, 1983; Whitfield & Slatter, 1979), product design (Hekkert, Snelders & van Wieringen, 2003; Veryzer & Hutchison, 1998), video screen presentations of (composite) faces (Langlois & Roggman, 1990; Langlois, Roggman & Musselman, 1994), photographs of parks (Herzog & Stark, 2004), Munsell glossy-finish colour chips (Martindale & Moore, 1988), semantic categories of natural objects (Martindale, Moore & West, 1988), representational paintings—surreal painting (Farkas, 2002), and Black & White slides of cubist paintings depicting human figures (Hekkert & van Wieringen, 1990)—as well as drawings of dogs, watches, birds, fish, and automobiles (Halberstadt & Rhodes, 2000, 2003).

In line with Whitfield’s (1983) initial suggestions, Hekkert and van Wieringen (1990) found a positive monotonic function between beauty and prototypicality for paintings for which the participants found it easy to identify the depicted figure as a human being. Conversely, this effect was not found for paintings with abstract human forms. Instead, there was an inverted U-shaped Beauty-Complexity function for the latter, but not for the former paintings. Martindale, Moore and Borkum (1990) reported similar results for a set of abstract shapes. They concluded that inverted U-shaped relationships are more likely for less typical stimuli, whereas positive, monotonic relationships are more likely for more typical stimuli. Moreover, that:

“... the determinants of preference tend to combine in a way such that the most important determinant overshadows other determinants. For example, if stimuli vary in both complexity and size, complexity accounts for most of the variation in preference. However, if stimuli also vary in meaningfulness or typicality, these [sic] account for most of the variation in preference and the contribution of complexity becomes negligible” (p. 75).

Similarly, Brant, Marshall and Roark (1995) did not find any relationship between a liking-scale and prototypicality for random asterisk patterns. Nevertheless, Herzog and Stark’s (2004) results, for environments that are positively or negatively valued, suggest that the positive monotonic Preference-Prototypicality function is only found for categories of positively...
2.3. The Preference-for-Fluency Model

Reber, Schwarz and Winkielman (2004; Winkielman, Schwarz, Fazendeiro, & Reber, 2003) noted that not only prototypicality, but also visual priming, presentation duration, and figure-ground contrast produce positive affect. First, they propose that these factors may be subsumed under the summy term ‘fluency’, referring to the ease with which an individual may process perceptual and conceptual information. Second, that fluency is hedonically marked and associated with positive affect, which results in favourable evaluations of stimuli. Third, that the fluency-preference link exists because fluency indicates that the individual has encountered the stimulus before; that it is familiar, predictable and unlikely to be harmful. Specifically, that high fluency indicates progress towards successful recognition and interpretation of the stimulus, which may lead to preference. Consequently, experts prefer complex pictures relatively more interesting. Ability to comprehend ambiguous, unexpected, or otherwise hard to classify; and (2) a coping potential appraisal, in which people judge whether or not they can comprehend the uncertain stimulus. Silvia (2005a, 2005b) found that interest in a piece of art depends on both these appraisal components. This means that interest requires that a person appraises the piece of art as uncertain but comprehensible.

Moreover, Reber and his colleagues propose an interaction between perceptual and conceptual fluency. While complexity represents a decrease in perceptual fluency, complexity may also facilitate access to the meaning of the stimulus, which may lead to preference. Consequently, experts prefer complex stimuli because the conceptual fluency overrides the perceptual fluency. However, if experts have a higher capacity to process information, as compared to novices, and there is a positive and monotonic relationship between fluency and preference, why do experts not prefer even simpler stimuli than the novices as these stimuli would be even easier for the experts to process as a result of their higher capacity? In order to deal with this reasonable objection, Reber and his colleagues suggests that experts are more likely than novices to consider aesthetic value, the ideas behind the work and the norms of ‘good’ and ‘bad’ taste. Therefore, experts may evaluate simple stimuli more negatively than novices, despite the pleasure they receive from easy processing.

2.4. Silvia’s Appraisal-of-Interest Model

Recently, Paul Silvia has explored how appraisal theory may inform psychological aesthetics, and developed the Appraisal-of-Interest Model (e.g., Silvia, 2006b). He has pointed out that the research on Berlyne’s Collative-Motivational Model and the Preference-for-Prototypes Model has not explored how individual differences arise. Importantly, a model based on stimulus properties, like arousal potential, cannot explain why people respond differently to the same aesthetic entity, or why a person may respond differently to an aesthetic entity over time.

Appraisal theory asserts that responses to aesthetic entities stem from psychological evaluations (Silvia, 2005a, 2005b, 2005c, 2006a). People’s thoughts about aesthetic entities are thus the immediate causes of responses. Consequently, the explanation of individual differences is that people appraise the same aesthetic entity differently, and differently on different occasions, as well.

To illustrate this point, Silvia (2005a, 2005b, 2005c, 2006a) conducted a series of experiments on interest in visual art, based on an appraisal model of aesthetic emotions that involves two appraisal components: (1) a *novelty check*, in which people appraise whether a stimulus is unfamiliar, complex, ambiguous, unexpected, or otherwise hard to classify; and (2) a *coping potential appraisal*, in which people judge whether or not they can comprehend the uncertain stimulus. Silvia (2005a, 2005b) found that interest in a piece of art depends on both these appraisal components. This means that interest requires that a person appraises the piece of art as uncertain but comprehensible.

Nonetheless, people differ both in how strongly the two appraisal components predict interest, and in the strength of the relationship between appraised uncertainty and interest (Silvia, 2005b). Moreover, Silvia (2006a) studied the influence of art training on interest. As expected, people with training in art found complex pictures relatively more interesting. Ability to comprehend complex pictures mediated the relationship between complexity and interest.
related motivational processes. Because Berlyne thought of Pleasantness and Interestingness as two independent factors, factor analysis suggested itself as a natural way to explore this idea. Berlyne (1974) and coworkers conducted several experiments applying factor analytic techniques to verbal scales by various stimuli. As expected, the first factor was most often Hedonic Tone (e.g., Pleasant, Good, and Beautiful). However, contrary to expectation the second factor was Uncertainty (e.g., Complex, Indefinite, and Disorderly), not Interestingness. The attribute ‘Interesting’ sometimes loaded on the first, sometimes on the second, and sometimes jointly on these two factors.

When investigating available data (e.g., Crozier, 1974), Eckblad noted that stimuli tended to organise themselves in their rank order of physical complexity in an ‘arc’ pattern around the origin in the score plot of the two factors (Eckblad, 1978, 1980). With support from Piaget’s (1950/1947, 1952/1936) theory of cognitive development, and Coomb’s (1964) theory of unfolding, the arc pattern gave Eckblad an idea of how to solve Berlyne’s problem.

According to Eckblad (1981a), it is cognitive schemes that mediate affective responses to stimuli, and not physiological arousal. In Eckblad’s view, schemes develop through four phases: (1) non-existence of scheme, (2) recognition scheme, (3) predictive scheme, and (4) habitual scheme. A recognition scheme is developed when a standard value (cf. prototype; e.g., Rosch, 1975) has taken form within the scheme. The scheme assimilates input by matching it against the standard value. A match between the standard value and input (successful assimilation) means recognition, whereas a mismatch means failure of recognition (i.e., the input is resisting assimilation). Further exposure to the stimulus, after that a recognition scheme is formed, leads to mastery. A predictive scheme is then developed when the scheme has organised relationships and consequences within its domain and has formed expectations. At this point, sets of expectations fulfil the function of standard values. As the scheme is elaborated successively, it may stop growing and become stable and habitual. A habitual scheme is the basis for automatic processes (cf. dual processing theory; e.g., Shiffrin & Schneider, 1977; Schneider & Shiffrin, 1977).

Depending on the complexity of stimuli and the person’s information processing capacity, input always resists assimilation to some degree, which causes affective responses (Eckblad, 1981a). The affective response depends on how elaborate the scheme is, and on the degree of assimilation resistance. Obviously, in a non-existent scheme, no responses are possible at all. As a standard value is formed, recognition produces pleasure (however, probably not in the case of intrinsically aversive stimuli; cf. ‘ecological properties’), whereas strong assimilation resistance may cause fear (e.g., a stranger to a child).

The most elaborate level is found in the predictive scheme. As full mastery of assimilation is reached, previously encountered stimuli become familiar. As a consequence of this increased capacity to process information, the person begins to appreciate a higher degree of assimilation resistance. Low degree of assimilation resistance is boring, whereas moderate degree of assimilation resistance causes pleasure, and still higher degree of assimilation resistance is interesting. As the assimilation resistance now continues to increase, the emotional response approaches confusion and anxiety, that is, stimuli are more and more unpleasant.

At the level of a habitual scheme, familiar objects are no longer consciously attended. For attention to occur, strong assimilation resistance is needed, which results in startle (cf. the orienting reflex; Sokolov, 1963). Such stimuli will dominate attention until they are recognised.

In consequence with her Cognitive-Motivational Model, Eckblad (1981b) proposed that physical complexity of Berlyne’s stimuli is positively and monotonically related to the assimilation resistance of the stimuli. That is, the more complex, the more the stimuli resist assimilation. The attributes ‘Boring’, ‘Pleasant’, ‘Interesting’, ‘Complex’ and ‘Unpleasant’ would therefore correspond to different ideal points along an assimilation-resistance dimension, which is represented by the arc pattern around the origin in the factor-score plot of the first two factors. This would explain Berlyne’s factor configurations, and in the factor-loading plot the attribute vectors would indicate where the ideal points are located along the assimilation-resistance dimension.

That the attribute ‘Interesting’ sometimes loaded on Hedonic Tone and sometimes on Complexity may depend on individual differences in the capacity to process information as a consequence of how well-developed schemes the individual holds in the particular domain. Eckblad (1980) proposed that individuals who find less complex stimuli interesting have a lower capacity to process information than individuals who find more complex stimuli interesting. In two separate experiments, Eckblad (1981b) and associates (Kroonenberg & Snyder, 1989) tested a principal components model based on the Cognitive-Motivational Model, which was corroborated.
3. Aesthetic Appreciation is Grounded in Information Processing

Together, the five models presented in the previous chapter provide important insights on what factors may determine aesthetic appreciation: (1) arousal potential primarily in the form of collative variables of stimuli (e.g., uncertainty or complexity), (2) prototypicality of the stimuli or, broader, (3) their processing fluency, (4) cognitive appraisal of novelty-complexity of stimuli and coping potential, and (5) assimilation resistance. The differences between the five models may be understood in relation to the concept of ‘information’, particularly the amount of information of stimuli, as a stimulus property, and people’s capacity to process this information, as a psychological factor (Table 1). In the present doctoral thesis ‘information’ is a technical term referable to Claude Shannon’s information theory (cf. entropy; Shannon & Weaver, 1949) that inspired much of the early research in psychological aesthetics (see e.g., Moles, 1968/1958). In particular, it inspired Berlyne to introduce the collative variables (Konecni, 1996).

For the purpose of the present doctoral thesis, ‘amount of information’ refers to perceptual or conceptual complexity of stimuli, or occurrence of unexpected events, in the same way as Shannon defined information, or entropy, as occurrence of the improbable (cf. ‘information rate’; Mehrabian & Russell, 1974), (Table 1). For example, the more objects a photograph depicts, or the more difficult it is to identify the motif, the more information the photograph contains. For sound, the amount of information is chiefly related to the number and sequences of events. A monotonous sound where the same kind of event occurs repeatedly, like the continuous sound of a ventilation fan, is low in information, whereas a chaotic sound with a more or less random sequence of unpredictable events, like the acoustic environment heard at a busy street corner, is high in information.

An individual’s capacity to process information refers to the capacity to deal with uncertainty and to comprehend stimuli (Table 1). This capacity is relative. The individual may have a relatively high capacity to process information in a domain (e.g., photography), compared to another person, but a relatively low capacity in another domain (e.g., sound art), compared to the same person. We may estimate the capacity to process information in a particular domain, by presenting a given set of stimuli, varying in the amount of information, to a group of persons. Because the set of stimuli is held constant, individual differences in responses to the set chiefly depend on the individuals’ processing capacity. We would conclude that individuals who find the set of stimuli easy...
to process have a relatively high capacity in the particular domain, and vice-versa (see Paper III for a detailed operationalisation).

Berlyne’s Collative-Motivational Model, which in essence is a stimulus-response model, suggests that the amount of information of stimuli (i.e., stimulus properties) determines aesthetic appreciation by mediation of physiological arousal. A fixed, ideal, moderate amount of information corresponds to aesthetic appreciation, hence the inverted U-shaped relationship. As Silvia (e.g., 2005c) points out, it is hard to comprehend how this model would explain individual differences in aesthetic appreciation. Two individuals exposed to the same aesthetic entity are exposed to the same stimulus properties, which represent the amount of information. Because the amount of information is supposed to determine aesthetic appreciation, the two individuals—who are exposed to the same aesthetic entity and consequently to the same amount of information—ought to have the same aesthetic appreciation to that entity. Consequently, to falsify Berlyne’s model, it is sufficient to prove that individual differences in aesthetic appreciation exist. Although the existence of such differences may seem obvious, Berlyne may not have realised that his model suffers from this weakness.

In contrast to Berlyne’s model the Preference-for-Prototypes Model implies that aesthetic appreciation depends on people’s capacity to process information—by an implicit assessment of how prototypical the stimuli are—and not on the amount of information of the stimuli per se. This model assumes that there is a negative, monotonic relationship between capacity to process information and aesthetic appreciation, that is, the less amount of information the better.

Research on the Preference-for-Prototypes Model illuminates three critical method limitations in psychological aesthetics. First, researchers typically recruit psychology undergraduates, who have no or little aesthetic experience or training. As we will see, professionals with aesthetic training perceive aesthetic entities noticeably different in comparison to novices (Paper III). Second, stimulus selection is often restricted to either typical or atypical entities, a limitation known as ‘restriction of range’. Third, there is a lack of consensus regarding the choice of dependent variable. The name of the Preference-for-Prototypes Model implies that preference ought to be the dependent variable. This is seldom the case. Instead researchers frequently use scales such as Like–Dislike (e.g., Martindale, Moore & Borkum, 1990; Farkas, 2002), Beautiful–Ugly (e.g., Hekkert & van Wieringen, 1990; Hekkert, Snelders & van Wieringen, 2003), and Attractive–Unattractive (e.g., Langlois & Roggman, 1990; Halberstadt & Rhodes, 2003) as substitutes for measures of preference. Taken together, these three method limitations restrict the empirical results we may obtain and make the validity of the empirical results of the research on the Preference-for-Prototypes Model questionable.

Silvia’s Appraisal-of-Interest Model integrates the amount of information of stimuli (cognitive appraisal of novelty-complexity) and people’s capacity to process information (cognitive appraisal of coping potential). The model proposes that processing capacity mediate the relationship between the amount of information and interest in aesthetic entities. This interaction is supposed to result in an inverted U-shaped relationship between the amount of information and interest. That is, interest in an aesthetic entity corresponds to an ‘ideal amount of information’. Moreover, people with a high processing capacity—for example, as a result of training—are relatively more interested in entities of a high amount of information compared to people with a low capacity. A major limitation of Silvia’s model is that it only predicts people’s interest in aesthetic entities. This means that we need a new and possibly different model if we want to understand other aesthetic outcomes. Therefore, it is not surprising that Silvia and Brown (2007) present an alternative model to account for appraisal of adverse aesthetic emotions.

In agreement with the Preference-for-Prototypes Model and in close correspondence to Silvia’s Appraisal-of-Interest Model, Eckblad’s Cognitive-Motivational Model assumes that people’s capacity to process information determines aesthetic appreciation, not the amount of information of stimuli as such. The capacity to process information differs from one individual to another, as a result of previous experiences and practice. Therefore, aesthetic appreciation corresponds to an ideal amount of information, but this amount is different for different individuals and different on different occasions. People with limited capacity to process information prefer a low amount of information whereas people with a high capacity find reward in the challenge and therefore prefer a high amount of information. This also means that as an individual learns how to master information in a particular domain, the ideal amount of information, corresponding to aesthetic appreciation, will increase [cf. Dweck’s (2006) research on children’s implicit personality theory of intelligence].

In order to progress psychological aesthetics, we need a model that integrates the different factors that underlie aesthetic appreciation and is consistent with empirical knowledge. With this notion in mind I explored this field. In the next chapter, I present my empirical findings.
4. My Empirical Results Support Integration of Previous Models

4.1. I aim to develop a new model of aesthetic appreciation

The overarching aim of the present doctoral thesis is to develop a new model of aesthetic appreciation that is consistent with empirical knowledge in psychological aesthetics and also would answer the question: What factors determine aesthetic appreciation?

I approached this objective by three empirical studies on aesthetic appreciation of photographs and soundscapes (Papers I–III). The specific research questions addressed in these three studies were:

1. What attributes are the major determinants of ‘aesthetic appeal’ of photographs (Paper I)?
2. Which are the main dimensions underlying soundscape perception (Paper II)?
3. What attributes may best explain individual differences in preferences to photographs, in regard of capacity to process photographic information (Paper III)?

Below, the most central results obtained in these studies are presented in summary. The interested reader finds the full texts of Papers I–III at the end of the present doctoral thesis.

4.1.1. Towards a psychology of photography (Paper I)

In Paper I “Towards a psychology of photography”, two interlinked experiments were conducted in order to explore what attributes are the major determinants of aesthetic appeal of photographs (i.e., ‘aesthetic appeal’—‘tilltalande’ in Swedish—was used as operational definition of ‘aesthetic appreciation’). In Experiment 1 of Paper I, 34 psychology undergraduates individually (1) sorted 564 photographs into mutually exclusive groups of similar amount of aesthetic appeal, (2) scaled their own sorted groups of photographs on aesthetic appeal, and (3) described what qualities they perceived in each of their own groups of photographs. The third and last step guarantees that individual interpretations of ‘aesthetic appeal’ are properly taken care of in the experiment. Based on the average aesthetic-appeal-scale values, a sub-set of 50 photographs, out of
the 564, were selected for further analysis. From the sorting data, a distance matrix for the 50 photographs was created. This matrix was subjected to a Multidimensional Scaling analysis (Coxon, 1982), which resulted in three multidimensional-scaling dimensions, interpreted with the aid of a subsequent Experiment 2. From analysis of the 34 participants’ qualitative descriptions of their own groups of photographs, 189 Swedish adjectives emerged. All these were related to perceived affective and conceptual qualities of the photographs. By the aid of 10 university students, the set of 189 adjectives were improved and reduced into a set of 141 unidirectional attribute scales, which were applied in Experiment 2.

In Experiment 2 of Paper I, 100 university students scaled the sub-set of 50 photographs, from Experiment 1, by the aid of the 141 unidirectional attribute scales. Using average scale values across the participants for every photograph, all pairs of the 141 attribute scales were intercorrelated and the resulting correlation matrix subjected to a Principal Components Analysis (Reyment & Jöreskog, 1996). This resulted in six oblique components interpreted as: Hedonic Tone, Expressiveness, Planfulness, Amusingness, Eroticism, and Familiarity. In total, this solution explained 78 % of the variance in the correlation matrix. In order to interpret the multidimensional-scaling dimensions from Experiment 1, and to explore what factors may best predict aesthetic appeal, multiple linear regression analysis was employed. It revealed that the three multidimensional-scaling dimensions may be interpreted as: (1) Hedonic Tone-Familiarity, (2) Absence of colour, and (3) Expressiveness-Dynamics. This result indicates that people’s familiarity with the photographs, the type of photographs (Colour or Black & White) and the photographs’ dynamics determine aesthetic appeal of photographs, and that Hedonic Tone and Expressiveness mediate this relationship.

4.1.2. A principal components model of soundscape perception (Paper II)

In Paper II “A principal components model of soundscape perception”, the underlying dimensions of perceived affective and conceptual qualities of soundscapes were explored (‘soundscape’ denotes the acoustic environment as perceived and understood, by people, in context). Besides contributing to the understanding of soundscape perception, this experiment aimed at providing the scientific underpinnings of soundscape design, which is closely related to aesthetic appreciation. The same approach as in Experiment 2 of Paper I was used. By the aid of 30 university students, the set of 189 adjectives, from Experiment 1 of Paper I, was improved and reduced into a set of 116 unidirectional attribute scales, applicable to soundscapes. By the aid of the 116 unidirectional attribute scales, 100 university students scaled a set of 50 excerpts of binaural recordings of urban outdoor soundscapes. Using average values across the participants for every soundscape excerpt, all pairs of the 116 unidirectional attribute scales were intercorrelated, and the resulting correlation matrix subjected to a Principal Components Analysis. This resulted in three orthogonal principal components interpreted as: Pleasantness, Eventfulness, and Familiarity. In total these three components explained 74 % of the total variance in the correlation matrix: 50, 18, and 6 %, respectively. Because of the low variance in Familiarity, this component was disregarded, and the attention was turned to the first two. In plotting the component loadings of Pleasantness against the component loadings of Eventfulness, it was obvious that there existed two alternative components represented by the diagonals of the graph. These components organised the soundscape excerpts along two continua from chaotic to calm, and from monotonous to exciting (Figure 2). As will be shown in the present doctoral thesis this solution, for soundscape excerpts, is very similar to the solutions for photographs, although the components are rotated differently.

4.1.3. Individual differences in preferences to photographs (Paper III)

Paper III “Individual differences in preferences to photographs” explored what attributes may best explain individual differences in preferences to photographs, in regard of information processing capacity. Based on the results of Papers I and II, 5 general concepts were developed as predictors of Preference (i.e., in line with current practice in psychological aesthetics, Preference was used as dependent variable and indicator of aesthetic appreciation):

Figure 2. Conceptual model of perceived affective qualities of soundscapes (corresponding to Figure 4 in Paper II).


Familiarity: Familiar–Unfamiliar, Common–Rare, Expected–Unexpected, Comprehensible–Incomprehensible.


As stimuli, 32 colour photographs were created. In order to reach a wide and varied range, the photographs were based on a 2 (presence/absence of humans) × 2 (presence/absence of artefacts) × 2 (presence/absence of nature) factorial design. Then, 10 psychology undergraduates, with no aesthetic training, and 5 photo professionals were recruited as participants. They were instructed to individually scale the 32 photographs on the 5 general concepts (predictors) and on Preference (dependent variable). Because Preference is a true collative variable, it is vital to allow comparison between the stimuli. For this reason the participants were instructed to organise the photographs along a visual analogue scale (1.5 m) in such an order that the distance between the photographs corresponded to how much they were preferred in relation to each other.

The results revealed statistically significant and systematic differences among the participants, related to their capacity to process photographic information, assuming that expertise represent a high capacity. In agreement with predictions, the photo professionals preferred photographs they perceived as uncertain and expressive, largely ignoring Familiarity and Hedonic Tone. Conversely, the psychology undergraduates preferred photographs they perceived as familiar and pleasant, largely ignoring Uncertainty and Expressiveness. Dynamics turned out to be a complicated concept and was thus disregarded in further data treatments. Individual analyses revealed that the participants found it hard to relate to this concept and used it rather idiosyncratically. Only one of the participants (a male student) gave it any weight in his preference judgments. In addition, analyses indicated that Dynamics, in general, had a low predictive ability, as the variance it explained in Preference largely overlapped with the variance explained by Uncertainty.

4.2. Future models in psychological aesthetics must handle individual differences

My empirical results are particularly challenging to Berlyne’s Collative-Motivational Model, because it is hard to comprehend how his model would be able to explain individual differences in aesthetic appreciation (Paper III). The results also show that the Preference-for-Prototypes Model is only partly true. It predicts well the responses of the psychology undergraduates who preferred a less amount of information. In contrast, this model does not predict the responses of the photo professionals who preferred a higher amount of information. Please bear in mind that the most typical participants in experiments in psychological aesthetic are psychology undergraduates, which probably explains why the Preference-for-Prototypes Model is popular.

Reber, Schwarz and Winkielman (2004) may be right on the account that experts experience pleasure from fluency. However, pleasure did not interest the photo professionals in Paper III. They preferred photographs they perceived as expressive. Probably, the latter has nothing to do with cultural norms or conventions of appropriate taste or aesthetic values, but rather with capacity to process photographic information.

Thus, my empirical results support an amalgamation of Silvia’s and Eckblad’s models, partly integrating the Preference-for-Prototypes Model. Conversely, Berlyn’s Collative-Motivational Model is irreconcilable with my results that show systematic individual differences in aesthetic appreciation. Taken together, my results lead me to propose an Information-Load Model, which will be outlined in the next chapter.
5. Towards an Information-Load Model

Empirical findings suggest that aesthetic appreciation is grounded in information processing, and particularly in the relationship between the amount of information of stimuli and people’s capacity to process this information. In agreement with Eckblad (1981a), I propose that information processing results in some degree of resistance, which increases with the amount of information of stimuli, and decreases with processing capacity. I label the resulting psychological factor Information Load, in the sense ‘demand on the individual’s cognitive-affective resources’ (Table 1), [see e.g., Damasio (1994) and Musch & Klauer (2003) for relevant discussions on cognition and emotion].

Whereas the amount of information of a stimulus may be absolute (cf. entropy; Shannon & Weaver, 1949), the degree of information load is relative:

1. Low degree of information load—the individual may find it easy to process a given amount of information because the individual has a relatively high capacity, or because the amount of information is low.
2. High degree of information load—the individual may find it hard to process a given amount of information because the individual has a relatively low capacity, or because the amount of information is high.

Also in agreement with Eckblad (1981a), I propose that Information Load causes affective responses to stimuli. At a low degree of information load, aesthetic entities are boring and inexpressive, at some higher degree of information load they are pleasant, and above a moderate degree of information load aesthetic entities are interesting and expressive. If the degree of information load exceeds the individual’s processing capacity, aesthetic entities are unpleasant. Moreover, aesthetic appreciation corresponds to a relatively low, optimal degree of information load for people with a limited capacity to process information (e.g., psychology undergraduates), compared to people with a high capacity (e.g., photo professionals). As an individual learns to master information in a particular domain (e.g., photography) the optimal degree of information load, which hypothetically corresponds to aesthetic appreciation, increases (cf. Paper III). Thus, this optimum depends on the individuals’ information processing capacity.
5.1. The Information-Load Model as a vector representation

Figure 3 presents the Information-Load Model in the form of an ideal, theoretic vector representation. The model represents an average across individuals, and illustrates the ideal configuration of the Information-Load Model in graphic form. The five vectors represent five general components: Aesthetic Appreciation (Aesthetic–Unaesthetic), Hedonic Tone (Pleasant–Unpleasant), Expressiveness (Expressive–Inexpressive), Uncertainty (Certain–Uncertain, in reverse), and Familiarity (Familiar–Unfamiliar). Uncertainty represents the perceived amount of information of stimuli. This corresponds to Silvia’s (2005c) novelty check, in which people appraise whether a stimulus is unfamiliar, complex, ambiguous, unexpected, or otherwise hard to classify. Familiarity represents the individual’s perceived capacity to process information. This corresponds to Silvia’s (2005c) coping potential appraisal, in which people judge whether or not they can comprehend the uncertain stimulus. Uncertainty and Familiarity are perceived conceptual qualities of stimuli and must not be confused with the actual amount of information of stimuli or the actual capacity to process information, which causes Uncertainty and Familiarity (cf. Section 5.2 below).

![Figure 3. The Information-Load Model, presenting the relationships between the five general components Aesthetic Appreciation (Aesthetic–Unaesthetic), Hedonic Tone (Pleasant–Unpleasant), Expressiveness (Expressive–Inexpressive), Familiarity (Familiar–Unfamiliar) and Uncertainty (Certain–Uncertain, in reverse) in the form of an ideal vector representation. Information Load is a latent factor that causes the five general components.](image)

In Figure 3 the general components are represented in the form of unit vectors, that is, the length of all vectors are one unit (i.e., 1.0) from the origin of the space. The angles (θ) between the vectors correspond to Pearson’s coefficient of correlations (r) between the scale values of the corresponding general components (r = cos θ), (Reyment & Jöreskog, 1996).

In a Principal Components Analysis, unit vectors, in terms of principal-component loadings, correspond to communalities (h²) equal to 1.0, which means that the values of the corresponding scales are perfectly explained in the model. In regard of the ideal, theoretic vector representation in Figure 3, this means that two principal components are sufficient to explain all the variance in the set of data, and that the representation corresponds to a two-dimensional geometric plane.

5.2. A model for measuring degree of information load

It follows from the Information-Load Model that a Principal Components Analysis of the measures of a set of stimuli—varying in degree of information load—on scales representing the five general components: Familiarity, Hedonic Tone, Aesthetic Appreciation, Expressiveness, and Uncertainty, would produce a two-component solution with the attribute vectors—corresponding to the scales—spread out in a fan-like configuration in the component-loading plot (cf. Coombs & Kao, 1960; Ecklad, 1981b). The order of the scale ends in the fan would be the same as the corresponding ideal points along the underlying ‘information-load dimension’ (i.e., Inexpressive, Familiar, Pleasant, Aesthetic, Expressive, Uncertain, and Unpleasant; see Figure 3). The information-load dimension would be represented in the component-score plot as a more or less circular curve around the origin, along which the stimuli are assumed to be located in the order of their degree of information load (Ecklad, 1981b; see Figure 3). This indicates that the relationship between any of the vectors, in Figure 3, and Information Load would be described by a sine function, as illustrated by Equation 1 and in Figure 4. I will use Aesthetic Appreciation as an example, but Equation 1 may be extended to any vector in Figure 3.

\[
\text{Aesthetic Appreciation} = \sin (\text{Information Load} - \varphi_{\text{Aest.}}),
\]

where \(\varphi_{\text{Aest.}}\) corresponds to the phase angle (see Figure 4), which is unique for every vector in the model. Because we operate with unit vectors, the amplitude of the function described by Equation 1 is equal to 1.0.

The degree of information load of stimuli is measured as the angular distance in arc-degrees, counter-clockwise, along the underlying information-load dimension in the principal-component-score plot, using the opposite pole of Aesthetic Appreciation as the 0-point (see Figure 3). This operation results in an information-load scale with arc-degree as unit (i.e., 0°–360°), (see Figure 4).
Equation 1 illustrates that Information Load is a higher order-latent factor that determines Aesthetic Appreciation (and all other perceived affective and conceptual qualities of aesthetic entities, as well). In addition, Equation 1 illustrates that Aesthetic Appreciation corresponds to an optimal degree of information load (Figure 4), or alternatively that Aesthetic Appreciation represents an ideal point on the underlying information-load dimension (Figure 3).

A latent factor is an element of a model that corresponds to an abstract concept (e.g., Hedonic Tone) or a psychological ability (e.g., intelligence) that causes behaviour (e.g., Bollen, 1989; Borsboom, Mellenbergh & van Heerden, 2003). The latent factor cannot be measured or observed directly, and in order to capture it, a set of manifest variables are aggregated in the model to represent the underlying construct. This may be done by Principal Components Analysis or similar techniques. For example, Hedonic Tone may be captured by aggregating the set of attribute scales: Pleasant–Unpleasant, Harmonious–Disharmonious, Tasteful–Tasteless, Comfortable–Uncomfortable, Appealing–Repulsive (see Paper III). Theoretically, the affective quality ‘hedonic tone’ of a stimulus may evoke a feeling of comfort that cause an individual to respond to the attributes in a certain way, for example, by scaling the stimulus as pleasant, harmonious, tasteful, comfortable and appealing. Thus, the five general components Aesthetic Appreciation, Familiarity, Uncertainty, Hedonic Tone, and Expressiveness, included in the Information-Load Model, are all latent factors, of the first order. As outlined above Information Load is more abstract and requires a higher-order aggregation.

5.3. The Information-Load Model in relation to previous models

All the five general components included in the Information-Load Model are previously known in psychological aesthetics. However, to my knowledge they have never before been integrated in the way presented in Figure 3. Importantly, the Information-Load Model follows directly from my empirical results (Papers I–III), independently from previous models, although the analyses used in Paper III were inspired by Eckblad’s work.

Berlyne (1974) explored the relationship between Hedonic Tone, Expressiveness (Interestingness) and Uncertainty (central to arousal potential). The Preference-for-Prototypes Model concerns the relationship between Familiarity (involving prototypicality) and Hedonic Tone. Silvia’s Appraisal-Of-Interest Model includes Familiarity, Uncertainty and Expressiveness. Because Eckblad (1981a) aimed at explaining an anomaly in Berlyne’s model, her Cognitive-Motivational Model includes Hedonic Tone, Expressiveness and Uncertainty, although she also discusses Familiarity and Aesthetic Appreciation. Yet others have proposed that Aesthetic Appreciation is directly dependent on Hedonic Tone and Expressiveness (e.g., Humphrey, 1972, 1973; see also Schmidhuber, 2007).

To summarise: Based on my empirical results (Papers I–III), I propose an Information-Load Model, incorporating the five general components Aesthetic Appreciation, Hedonic Tone, Expressiveness, Familiarity, and Uncertainty. The first three components, Aesthetic Appreciation, Hedonic Tone, and Expressiveness, represent affective responses to stimuli, or perceived affective qualities. Familiarity represents the individual’s perceived capacity to process information, whereas Uncertainty represents the perceived amount of information of stimuli. The latent factor Information Load causes the five general components. It is a latent factor in the sense that it corresponds to a higher-order construct that cannot be measured or observed directly. It is inferred through the response behaviour it causes, and it is measured as the angular distance in arc-degrees along the underlying information-load dimension, which results from a Principal Components Analysis of measures of the five general components. Thus, my thesis is that Information Load is the key factor underlying aesthetic appreciation.
6. Information Load is the Key Factor Underlying Aesthetic Appreciation

In order to validate my thesis, that Information Load is the key factor underlying aesthetic appreciation, I re-examined the data presented in Papers I–III. Based on Coombs’ theory of unfolding (Coombs, 1964; Coombs & Kao, 1960), Eckblad (1981b) predicted that Principal Components Analysis has the capacity to reveal if Information Load is at play.

First, as outlined in Section 5.2 above, the attribute vectors in the component-loading plots of the first two principal components should be organised in a meaningful pattern along the perimeter of the plot in the order they represent increasing degree of information load, for example, ‘Inexpressive’, ‘Certain’, ‘Familiar’, ‘Pleasant’, ‘Aesthetic’, ‘Expressive’, ‘Uncertain’, ‘Unfamiliar’, and ‘Unpleasant’. Ideally, ‘Familiar’ would appear opposite to ‘Unfamiliar’, ‘Pleasant’ opposite to ‘Unpleasant’, ‘Expressive’ opposite to ‘Inexpressive’, and ‘Certain’ opposite to ‘Uncertain’ (see Figure 3). This configuration would show that there are no problems caused by non-linear relationships between the attribute scales included.

Second, inspection of the component-score plots ought to reveal a sector in the graphs in the shape of ‘a piece of a pie’ that is empty of data points. This is where the two endpoints of the underlying information-load dimension are supposed to meet in the graphs. That is, between the attribute vectors ‘Unpleasant’, which corresponds to extremely high degree of information load, and ‘Boring’, which corresponds to extremely low degree of information load. This part of the graphs is supposed to be empty because the endpoints of the information-load dimension are unlikely to overlap in the principal-component solution and, in theory, no data points ought to exist outside the range of the information-load dimension. Naturally, other parts of the component-score plots may be more or less empty of data points as well, that is, if there are few data points in the graphs.

In re-examining the data from Papers I–III, the results of the Principal Components Analyses of Experiment 2 of Paper I, as well as, the experiment of Paper II are straight forward to use. To facilitate the comparison, I will present all results in the form of figures. For Paper III, I re-analysed the data and conducted a new Principal Components Analysis following the same procedure as in Papers I and II. I used average group data, and extracted the orthogonal principal components without applying any rotation (see Papers I and II for details). This means that I collapsed the data for psychology undergraduates and photo professionals. This was motivated, because the
variation, both within and between the two groups, was sufficient and slightly overlapping (see Figure 3 in Paper III). In addition, average group data reduces the risk that potential outliers will affect the results.

Figures 5–7 present the principal-component loadings of the first two orthogonal principal components of Experiment 2 of Paper I, as well as, the experiments of Paper II and Paper III, respectively. The left panel of Figure 8 presents the corresponding principal-component scores of Experiment 2 of Paper I, and Figure 9 and 10 present the corresponding scores of the experiments in Paper II and Paper III, respectively. The multidimensional-scaling solution presented in the right panel of Figure 8 will be discussed in Section 6.5 below.

Part of the results presented in Figure 5 was presented in Table 4 of Paper I. Here the complete result of the first two principal components is presented. Figure 6 corresponds to Figure 1 of Paper II, and Figure 9 corresponds to Figure 4 of Paper II. The results presented in Figure 7, the left panel of Figure 8, and in Figure 10 have not been published previously.

As predicted, visual inspection of the loadings of the first two principal components of the experiments in all three papers (Papers I–III; Figures 5–7) reveals that the attributes associated with different degrees of information load are distributed throughout the perimeter of the graphs in the expected meaningful circular order, an observation I will return to below. First I will examine the attribute scales. Importantly, the attribute scales used in the present set of experiments were selected based on the empirical results obtained in Experiment 1 of Paper I. Thus, this large set of attributes has its origin in how people perceive aesthetic entities, independently from the present theoretic framework.

6.1. People can verbalise degree of information load

When the 34 participants in Experiment 1 of Paper I were asked to describe what qualities they perceived in the 564 photographs, which they had organised along an aesthetic-appeal scale, they produced a set of attributes that correspond to different degrees of information load. The photographs assigned to the lowest values of aesthetic appeal were most frequently described as “Sickening” or “Unpleasant”, which correspond to extremely high degree of information load. Towards the middle of the aesthetic-appeal scale the number of negative expressions decreased in favour of expressions like “Meaningless”, “Insignificant”, “Boring”, “Uninteresting”, or “Dead”, which all correspond to extremely low degree of information load. In the upper half of the aesthetic-appeal scale, expressions like “Commonplace” and “Neutral” occurred. Closer to the top of the aesthetic-appeal scale, the photographs were all more often described as “Funny”, “Warming”, “Harmonious”, “Expressive” or “Thought-Provoking” (Table 1 in Experiment 1 of Paper I). In agreement with the Information-Load Model, this response pattern suggests that entities that are low in aesthetic appreciation are unpleasant and expressionless. Entities that are moderately aesthetic are familiar or complex, whereas entities high in aesthetic appreciation are pleasant and expressive (see Figure 3).

In analysing the interview notes from Experiment 1 of Paper I, it occurred to me how systematic the outcomes were across the 34 participants. After analysing the notes from the first ten interviews it was apparent that although the participants had different views on different photographs, the participants described the photographs, along the aesthetic-appeal scale, in similar ways. For example, regardless of what photographs a participant placed at the upper extreme of the scale, photographs that the participants found to be aesthetically appealing were typically described as harmonious, expressive and thought-provoking.

6.2. Attributes related to aesthetic appreciation are ordered along the information-load dimension

The attributes, corresponding to different degrees of information load, generated in Experiment 1 of Paper I, are found along the perimeters of the component-loading plots in Figures 5–7. They are chiefly located on the perimeters, and not in the centres, of the graphs, which shows that most of the variance in the attribute measures is explained by the first two principal components. This provides support to the Information-Load Model and its postulate that Information Load is the key factor underlying aesthetic appreciation.

Please observe that the order of the attribute vectors along the perimeter of the plots (Figures 5–7) are more important than the two orthogonal principal components, which we normally would aim to interpret (cf. Eckblad, 1981b). The angles (θ) between the vectors in these graphs correspond to the correlation \( r = \cos \theta \) between the corresponding attribute scales, and the angles depend on individual differences in capacity to process information in different domains (Paper III; Eckblad, 1980). Consequently, we would expect different principal-component solutions, also at group level, from qualitatively different sets of data. The different group-level results for photographs and soundscape in Papers I–III, presented in Figures 5–7, support this view. The principal components presented in Figure 5 may be interpreted as Hedonic Tone and Expressiveness, the principal components presented in Figure 6 as Hedonic Tone and Eventfulness, whereas the principal components presented in Figure 7 may be interpreted as Familiarity and Eventfulness/Dynamics. What solutions we obtain from a Principal Components Analysis depend on which components explain the most of the variance in the data set. To expect that these components always would be the same is overoptimistic. However, according to the theoretic framework, the order of the attribute vectors along the perimeter of the principal-component-loading plot—or rather the oblique components they represent—ought to be stable.
Imagine a vector as an arrow pointing at a data point from the origin of the graph in the principal-component-loading plots. As seen in Figure 7, the vectors representing similar attributes cluster in the graph. In order to guide the reader, I have encircled data points that represent the same oblique components, that is, Familiarity, Hedonic Tone, Expressiveness, Dynamics, and Uncertainty (see Table 1 of Paper III). Please observe that ‘Provoke imagination’ is strongly associated with the three components: Uncertainty, Expressiveness and Dynamics. ‘Aesthetic’ is almost equally associated with Hedonic Tone and Expressiveness (cf. Humphrey, 1972, 1973), and ‘Preference’ was used as dependent variable in Paper III and originally not included in the Principal Components Analysis. For these reasons I have chosen not to encircle these attributes in Figure 7.

Although the individual vectors are not likely to be organised in a specific order, the oblique components they represent are obvious and straightforward. With a little effort, we may discern similar patterns in Figures 5 and 6 (for readability, not all 141 vectors are labelled in Figure 5). In Figure 5, which presents photography data from Experiment 2 of Paper I, attribute vectors representing the opposite pole of Expressiveness cluster at the bottom of the graph (e.g., ‘Vapid’, ‘Boring’, ‘Uninteresting’, and ‘Expressionless’). A corresponding cluster is found at the bottom left of Figure 6, presenting soundscape data from Paper II. Following the perimeter of the two graphs, counter-clockwise, we discover that the patterns of the vectors are almost identical in Figures 5 and 6. Immediately to the right of the first cluster, in both figures, we find a cluster of vectors representing the opposite pole of Eventfulness (e.g., ‘Static’, ‘Uneventful’, and ‘Immobile’). This cluster is followed by Calmness (e.g., ‘Quiet’, ‘Calm’, ‘Tranquil’, ‘Peaceful’, and ‘Soothing’). In Figure 5 the latter component intersects with Familiarity (e.g., ‘Common’, ‘Conventional’, ‘Familiar’, and ‘Comprehensible’). Probably because of the low variance in this component in Paper II (soundscape perception), Familiarity is found in the centre of the graph in Figure 6. After Calmness follows: Hedonic Tone (e.g., ‘Pleasant’, ‘Harmonious’, ‘Comfortable’, and ‘Appealing’), Expressiveness (e.g., ‘Expressive’, ‘Interesting’, ‘Fascinating’, and ‘Meaningful’), Eventfulness or Dynamics...
(e.g., ‘Eventful’, ‘Dynamic’, ‘Lively’, and ‘Mobile’), Uncertainty (e.g., ‘Complex’, ‘Ambiguous’, ‘Surprising’, and ‘Chaotic’), and finally the opposite pole of Hedonic Tone (e.g., ‘Unpleasant’, ‘Repulsive’, ‘Disharmonious’, and ‘Disgusting’). In Figure 5 the opposite pole of Hedonic Tone intersects with the opposite pole of Familiarity.

In summary, the identified oblique components in Figures 5–7 are: (1) Familiarity, (2) Calmness, (3) Hedonic Tone, (4) Expressiveness, (5) Eventfulness/Dynamics, and (6) Uncertainty, in this order. There are two exceptions. As noted above Familiarity has detached itself from the model in Figure 6 and is found in the centre of the graph. In Paper III, Calmness was not included (Figure 7). The oblique components in Figures 5–7 are exactly in the predicted order along the information-load dimension. This is remarkable considering that these empirical results were obtained in experiments using two completely different kinds of stimuli; photographs in Papers I and III, and soundscapes in Paper II.
6.3. A gap in the principal-component solution indicates Information Load

Eckblad (1981b) predicted that we ought to find an empty sector in the component-score plots between the two endpoints of the information-load dimension. The left panel of Figure 8 presents the principal-component scores on the first two orthogonal principal components of the 50 photographs scaled in Experiment 2 of Paper I. The corresponding principal-component loadings of the 141 attribute scales used in this experiment are found in Figure 5. Inspection of the left panel of Figure 8 shows that the data points, representing the 50 photographs, are rather evenly distributed throughout the graph. Nevertheless, in the bottom left quadrant we find an empty sector in the shape of a piece of a pie, marked gray. Comparing the left panel of Figure 8 with Figure 5 reveals that this sector of the graph is exactly the part where the information-load dimension is supposed to begin and end. This is where we find attributes like ‘Meaningless’, ‘Lifeless’, and ‘Boring’, on the one hand, and ‘Unpleasant’, ‘Disgusting’, and ‘Repulsive’, on the other, in Figure 5.

Figure 9 presents the principal-component scores on the first two orthogonal principal components of the 50 soundscape excerpts scaled in Paper II. Figure 6 presents the corresponding principal-component loadings of the 116 attribute scales used in this experiment. In Figure 9, three bipolar vectors represent the attributes: ‘Simple vs. Complex’, ‘Pleasant vs. Unpleasant’ and ‘Boring vs. Interesting’. In addition, the circular arrow represents the information-load dimension.

As expected, an empty sector appears in Figure 9 where the information-load dimension is supposed to begin and end. As in the left panel of Figure 8, this is the only sector of the graph that is devoid of data points. The same result is apparent in Figure 10, which presents the principal-component scores on the first two orthogonal principal components of the 32 photographs scaled in Paper III. The corresponding principal-component loadings of the 27 attribute scales used in this experiment are presented in Figure 7. Because the density of data points is lower in Figure 10, than in Figures 8 and 9, there are some additional parts of the graph that are lacking data points, for example, between the opposite pole of ‘Uncertainty’ and ‘Familiarity’, as well as,
between ‘Uncertainty’ and the opposite pole of ‘Familiarity’. This presents no
problem to my argument, because the expected part of the graph is empty of
data points, which supports the Information-Load Model.

In summary: First, people are able to verbalise their experience of different
degree of information load, in the form of attributes. Second, both the
predictions regarding the results of a Principal Components Analysis of a set
of scales based on such attributes are true for all the three experimental studies
included in the present doctoral thesis (Papers I–III). The oblique components
are organised along the perimeter of the principal-component-loading plots
in the meaningful circular order that corresponds to increasing degree of
information load. Moreover, there is an empty sector in the shape of a piece
of a pie in the principal-component-score plots, where the information-load
dimension is predicted to begin and end.

6.4. Information Load represents something real

With the purpose to make these results tangible, Figure 11 presents four
photographs from Paper III. These photographs are marked A, B, C, and D in
Figure 10. Among all 32 photographs in Paper III, Photographs A and B are the
lowest in degrees of information load, Photograph C was on average the most
preferred among the 15 participants in Paper III, and Photograph D has the
highest value in the information-load dimension. Photograph A is interesting,
because, in Figure 10, it is located between the opposite poles of Hedonic Tone
(i.e., ‘Unpleasant’) and of Expressiveness (i.e., ‘Boring’), which may indicate
that it falls outside the range of the information-load dimension. Photograph A
depicts a young female against a black backdrop in a photo studio as the photo
flash accidently hits the camera lens. Among photographers this would be
regarded as a failed photograph to be discarded.

In a lecture on my research results a man in the audience objected to the idea
that no aesthetic entity ought to fall outside the range of the information-load
dimension because it would be too simple and too complex at the same time.
He stated that this is exactly how he feels towards Picasso’s cubistic paintings.
They are both banal and visually complex, and at the same time completely
incomprehensible. Such an aesthetic entity would possibly fall outside the
range of the information-load dimension, because of the ambiguous feelings
it provokes.

According to Eckblad’s definition, Photograph B would be the lowest
in degree of information load. It is a still-life photograph of a set of office
equipment and a toy scooter against a white backdrop. Most people would
agree that this is a very simple photograph, although the toy scooter evokes
some interest. Photograph C depicts a section of Hadrian’s Wall in northern
England, located in rough and wild nature. The sky is overcasted by heavy rain-
clouds that make the photograph dark and dramatic. Photograph D is one of a
set of four photographs among the 32 photographs used in Paper III that was
created not to include any identifiable objects. These four photographs cluster
in Figure 10 and reach the highest values in the information-load dimension
among all the 32 photographs. They were created by randomising the location
of the pixels in the photographs. This made them extremely visually complex.
That these four photographs, including Photograph D, are the photographs that
have the highest values in the information-load dimension in Paper III, support
my operational definition of ‘information load’, beginning at the opposite pole
of Preference (dependent variable in Paper III). In addition, Photographs A–D
show that Information Load represents something real.

One question remains to explore: are the current results, based on semantic
scales and Principal Components Analysis, artefacts caused by the attributes
in combination with the statistical operation, or do the results represent how
people truly perceive aesthetic entities? In order to answer this question it
is necessary to employ a statistical technique that is not prone to create a

circular order, including the gap in the score plot, as in Principal Components

Analysis.

6.5. Information Load is independent of methods

In Experiment 1 of Paper I, the 34 participants did not only generate adjectives

in describing their perception of aesthetic appeal to photographs. Before the

interview they sorted the 564 photographs into mutually exclusive groups of

similar amount of aesthetic appeal, and placed their own sorted groups of

photographs along a visual analogue scale of aesthetic appeal. Calculating how

frequently a pair of photographs occurred in different groups of photographs,

across the 34 participants, I created a distance matrix which I subjected to

a Multidimensional Scaling analysis using a subset of 50 photographs. The

more often two photographs occurred in different groups the more dissimilar,
or distant, they were in aesthetic appeal.

The right panel of Figure 8 presents Dimensions 1 and 3 of the

Multidimensional Scaling analysis of the subset of 50 photographs (the original

solution is presented in the right panel of Figure 2 in Paper I). These two

dimensions correspond to the first two orthogonal principal components of the

Principal Components Analysis conducted on the same set of photographs in

Experiment 2 of Paper I (left panel of Figure 8). Please observe that in order to

facilitate comparison between the two solutions, I have reversed Dimension 1

of the multidimensional-scaling solution.

Figure 12 plots the degree of information load of the 50 photographs,
calculated based on the principal-component solution presented in the left
panel of Figure 8, against the degree of information load of the same set of
50 photographs, calculated based on the multidimensional-scaling solution
presented in the right panel of Figure 8. Because Photograph 22 was the
photograph lowest in degree of information load in the principal-component
solution, I selected its position as the 0-point of the information-load scale
for the two solutions. Thus, for every photograph in Figure 8 (left and right
panels individually) the degree of information load is calculated as the angular
distance in arc-degrees, in counter-clockwise order, from the position of
Photograph 22.

Figure 12 shows that the two solutions are highly in agreement. They only
differ for 5 out of the 50 photographs (Photographs 20, 28, 44, 46 and 48, see
open circles in Figure 12). Whereas the 100 participants in Experiment 2 of
Paper I assessed Photographs 20, 44 and 46 to be high in degree of information
load, in terms of attribute scales, the 34 participants in Experiment 1 of Paper I
found these photographs very similar to photographs low in degree of
information load, in terms of similarity in aesthetic appeal. Please observe
that the Information-Load Model presented in Figure 3 predicts that entities
high (i.e., perceived as unpleasant) or low (i.e., perceived as boring) in degree
of information load are more or less similar in aesthetic appeal. Therefore,
it is not surprising to find that the exact location of the endpoints of the
underlying information-load dimension is indistinct in the multidimensional-
scaling solution (see the curved line in the right panel of Figure 8), because
this solution is based only on perceived aesthetic similarity. In contrast, the
location of the two endpoints in the principal-component solution is clear-cut
and well defined by ‘Unpleasant’ and ‘Boring’. This explains the lack of an
empty slot in the multidimensional-scaling solution (right panel of Figure 8).

Similarly, Photographs 28 and 48 are located close to the origin in the
upper right quadrant in the left panel of Figure 8, and would be considered
as moderate in degree of information load. In comparison, the 34 participants
in Experiment 1 of Paper I perceived these photographs as more similar to
photographs low in degree of information load.

The (trimmed) Pearson’s coefficient of correlations for the remaining
45 photographs in Figure 12 (filled circles) was 0.95 ($p < 0.001$). This high
 correlation coefficient between the two information-load scales, based on (1) the
principal-component solution and (2) the multidimensional-scaling solution,
was obtained although the two solutions were created by two different groups of participants using two different methods of data collection. This result shows that Information Load is independent of methods, including methods of data collection and statistical analyses. In addition, the result suggests that the measure of degree of information load, as the angular distance around the two-dimensional principal-component space, is valid.

7. Information Load is a Fruitful Concept

7.1. Information Load is not an artefact

Because the information-load dimension is proposed to be a more or less circular curve around the origin of the score plot of the first two principal components, it is tempting to suggest that it simply is a horseshoe (Kendall, 1970) or Guttman (1968) effect. This is a phenomenon associated with Multidimensional Scaling and Principal Components Analysis, and similar multivariate statistical techniques (Diaconis, Goel & Holmes, 2008; Podani, & Miklós, 2002). Sometimes the primary dimension or principal component folds itself in the first two dimensions of the results, and what should have been one straight dimension is represented as an unmistakably horseshoe-shaped curve occupying two dimensions instead of one. This is typically thought of as an artefact of the statistical technique, and statisticians have attempted to develop new statistical methods that do not suffer from this ‘imperfection’ (e.g., van Eck & Waltman, 2007). However, in the present case, making claims for the horseshoe effect would purely be based on theoretical reasoning. Obviously, there is no horseshoe-shaped curves observable in any of the results reported above (Figures 8–10). Even though the data points may scatter, typically the density of the data points in the horseshoe increases towards the periphery (Buja & Swayne, 2002). The vast scatter observed in Figures 8–10 is not typical for the horseshoe effect. Moreover, it is difficult to believe that the horseshoe effect would occur systematically in four independent experiments. Thus, although the information-load dimension resembles the horseshoe effect in theory, as both describe a curvilinear function of the first two dimensions of a multivariate statistical analysis, Information Load is clearly not an artefact caused by the statistical procedure, but a valid result.

7.2. Aesthetic appreciation is properly measured and mapped

My thesis rests on the assumption that I have properly measured aesthetic appreciation and mapped its underlying dimensions. What is the validity of this assumption?

Predominantly, this question relates to Experiment 1 of Paper I, in which I mapped the underlying dimensions of aesthetic appeal of photographs, by Multidimensional Scaling, and generated the attributes used in the subsequent experiments. I discuss this question in detail in Paper I. In particular I
7.3. Perceived affective qualities are similar for soundscapes and places

The present results, particularly the results on soundscapes, are very similar to those obtained by Russell and his colleagues who found that perceived affective qualities of places may be described by a two-dimensional model defined by four bipolar dimensions located 45° apart (e.g., Russell & Pratt, 1980; Russell, Ward & Pratt, 1981). Based on Russell’s research on core affect (e.g., Russell, 1980, 2003), Russell and his colleagues interpreted the eight poles of this model as: pleasant (0°), exciting (45°), arousing (90°), distressing (135°), unpleasant (180°), gloomy (225°), sleepy (270°) and relaxing (315°). Alternatively, the model may be regarded as representing two orthogonal bipolar dimensions of Pleasant–Unpleasant and Arousing–Sleepy, or equally well of Exciting–Gloomy and Distressing–Relaxing (Figure 13; cf. Figure 2).

Comparing the results that Russell and his colleagues obtained with the present results on soundscapes, it is reasonable to reinterpret Russell and his colleagues’ results. Figure 14 presents the loadings on the first two orthogonally rotated factors that Russell, Ward and Pratt (1981) obtained when they asked 323 participants to individually scale a different place, in situ, on 105 unidirectional attribute scales. The horizontal component is clearly Pleasant–Unpleasant. The vertical factor has a lot in common with the component I have labelled Eventfulness or Dynamics. For example, the attribute ‘Active’ load highly on this component. To call the vertical factor Arousing seems peculiar, because the attribute ‘Arousing’ load higher with ‘Exciting’. The same is true for other results on perceived affective quality of places that Russell and his colleagues have reported (e.g., Russell & Lanius, 1984). Moreover, Ward and Russell (1981) compared several ways of scaling places and found that ‘Active’ referred to the amount of activity observed in
a place, whereas ‘Arousing’ referred to an affective response to the place. Consequently, it seems reasonable to interpret the vertical factor of Figure 14 as Eventfulness, Dynamics or Activity. This shows that the model I and my colleagues proposed in Paper II, for describing perceived affective qualities of soundscape (Figure 2), is robust and applicable to environments in general, including their soundscape (see also Knez & Hygge, 2001; Västfjäll, Kleiner & Gärling, 2003).

7.4. Familiarity and Uncertainty are two separate components

Another interesting aspect of Russell’s research on perceived affective quality and core affect, is his use of ‘information rate’ in his early research. Mehrabian and Russell (1974) proposed that terms I have associated with Familiarity and Uncertainty, such as, ‘Novel’, ‘Complex’, and ‘Familiar’, may be subsumed by a single dimension, extending from the simplest, most familiar, and most predictable place, to the most complex, most novel, and most unpredictable place, at the opposite extreme. In contrast to Mehrabian and Russell, I keep Familiarity and Uncertainty separate, and do not mix them into a single ‘information-rate’ scale, although they had a high negative coefficient of correlation in the case of photographs (Paper III).

Martindale’s (1981) theorising agrees with my view that Familiarity and Uncertainty are two separate components. Eckblad (1981a) defined ‘assimilation’ as the process of matching an input to a standard value or expectation, and ‘assimilation resistance’ as the corresponding mismatch. In contrast, Martindale (1981) suggests that there are two kinds of match/mismatches. Novel, surprising, and incongruous stimuli involve a mismatch between an input and an expectation, whereas complex, conflicting, or ambiguous stimuli may match several standards, at least partially. I illustrate this in Figure 15, which depicts the three categories A, B and C as a Venn diagram. A and B are two partially overlapping categories, like ‘Chair’ and ‘Table’ for which ‘Stool’ may represent the intersect (A ∩ B). C represents a category of novel elements that are unfamiliar to the individual. If we, in agreement with Rosch, assume that a category has a central prototype and membership in a category is a matter of family resemblance with the prototype (Rosch & Mervis, 1975; Wittgenstein, 1953), uncertainty and complexity would increase with the distance to the prototype, and an element that belong to the intersect of two categories may be described as ambiguous. On the other hand, the prototypical element of the well-known category is familiar, simple, comprehensible, unambiguous, predictable, and so forth, whereas an element of Category C is unfamiliar, unexpected, unpredictable, and incomprehensible. The intersect of Categories A and B represents Uncertainty, whereas Category C represents the opposite of Familiarity, two clearly distinct, although related, components.

Figure 15 may help in understanding the results from the research on the Preference-for-Prototypes Model, which show a positive and monotonic Preference-Prototypicality function for familiar, every-day objects, as opposed to an inverted U-shaped function between Uncertainty and Hedonic Tone for complex stimuli. That is, this research demonstrates different types of relationships for different types of stimuli, depending on if stimuli are sampled from a familiar category, like Category A or B, or if they are sampled from the intersect of Categories A and B, which represents Uncertainty. Importantly, prototypical stimuli, close to the centre of Category A or B, are low in degree of information load, which then increases with the distance to the prototypical elements of these two categories as we move towards the perimeter, crossing the intersect and reaches the upper extreme of the underlying information-load dimension at the centre of Category C. This means that stimuli, in the research on the Preference-for-Prototypes Model, are sampled from different segments of the information-load dimension, which in turn means that the stimulus range is restricted. Figure 4 illustrates how it is possible to obtain different types of relationships for different stimulus segments along the information-load dimension. For stimuli low in degree of information load a positive monotonic function is most likely whereas an inverted U-shaped
function is more likely for stimuli of intermediate degree of information load, as demonstrated by the results on the Preference-for-Prototypes Model. I have previously criticised the research on this model for restricting the selection of participants to mainly psychology undergraduates. The two restrictions referred to in the present paragraph may account for the majority of the results in this research, and makes the validity of the Preference-for-Prototypes Model doubtful [cf. Eckblad’s (1981a) and Russell & Snodgrass’ (1987) critique of research on the mere-exposure effect].

7.5. Information Load connects attributes representing perceived affective and conceptual qualities

Another relevant aspect of Russell’s model of perceived affective quality of places is that every variable is interconnected with all the other variables. This is fundamental to Russell’s research on emotions, because he argues against the view that emotions or everyday feelings are best understood as a set of discrete and independent categories. Instead, Russell (e.g., 1980, 2003) argues that human emotions share two main components of core affect: Pleasantness and Activation. An emotional episode, like falling in love, being angry, or being nervous, represent a different combination of these two components. I would argue that these two components are the result of Information Load.

In an experiment on perceived affective quality of places, Russell and Lanius (1984) demonstrated how a shift in adaptation level cause a reverse shift in perceived affective quality of a target stimulus. This shift was reflected throughout the two-dimensional space and in all variables in Russell’s model (Figure 13). A shift of one unit in one variable corresponded to a shift in all the other variables in the model, proportional to the cosine of the angular distance between the variables. Although this result follows mathematically it deserves consideration, because it provides an excellent illustration of what it means that Information Load is a higher-order latent factor.

Figure 16 illustrates the theoretic principle. I have included five arrows (A–E) that represent five variables or scales. Between Arrows A and B, I have drawn two dots (1 and 2) that represent a shift in value of a stimulus (from position 1 to position 2). This shift in value is reflected on all the arrows as illustrated with dashed lines perpendicular to the arrows and intersecting at the two dots. Because all arrows correspond to unit vectors the shift on each arrow (e.g., from a1 to a2 on Arrow A) is proportional to cosine of the angular distance between the arrows (cf. r = cos θ).

Below, I extend this theoretic principle with an empirical example from Paper II on soundscape. Remember that the 100 participants in Paper II scaled the perceived affective and conceptual qualities of soundscapes on a set of 116 attribute scales irregularly ordered in a booklet. They did not move a dot in a circular model with predefined oblique vectors, as in Figure 16.

Figure 17 presents empirical data from Paper II. The upper panel illustrates that a shift of one unit in an independent variable (X), on average, results in a shift in the dependent variable (Y) equal to the regression coefficient (b) of the simple linear regression equation that describes the principal relationship between the two variables (Y = a + b × X). The lower panel illustrates that the regression coefficient (b) equals Pearson’s coefficient of correlations (r) between the two variables after they are standardised (M = 0, SD = 1), (i.e., ZY = rXY × ZX). From the above, we know that Pearson’s coefficient of correlations (r) equals cosine of the angle (θ) between two vectors (r = cos θ). In both panels of Figure 17, mean values are marked by two intersecting dashed lines. The solid diagonal lines are the regression lines, representing the estimated values of the regression equations.

In Figure 18, I illustrate Russell’s point that a shift of one unit in one variable results in a corresponding shift in all other variables in the model. From Paper II on soundscape, I have selected all attributes on the perimeter of Figure 6 with communalities (h²) larger than 0.7. I use the attribute vector ‘Meaningless’ as the starting point and move along the perimeter of Figure 6 in counter-clockwise order, which means along increasing degree of information load. The selection of ‘Meaningless’ as the starting point is justified, because
it is located 1.5° before ‘Boring’. I have calculated the angular distance from ‘Meaningless’ for every attribute vector included, and plotted this value on the Abscissa of Figure 18. As the next step, I conducted a complete series of simple linear regression analysis, using the scale values of ‘Meaningless’ as the only independent variable (X) and the values of all other included attribute scales as dependent variables (Y). On the Ordinate of the upper panel of Figure 18, I have plotted the resulting set of the regression coefficients (b). This means that the values on the Ordinate represent the corresponding shift in all other variable when the scale value of ‘Meaningless’ increases one unit in absolute scale-values, as illustrated with an example for the attribute scale ‘Ugly’ in the upper panel of Figure 17. On the Ordinate of the lower panel of Figure 18, I have plotted the values of the corresponding Pearson’s Correlation Coefficients (cf. the lower panel of Figure 17). The solid wave curve in both panels of Figure 18 is the cosine of the angular distance, representing the estimated values on the Ordinate (i.e., the predicted values of the regression/correlation coefficients between the scale values of ‘Meaningless’ and the values of all other included attribute scales) if the relationships had been ideal as in a unit circle with unit vectors. In both panels, the amplitude of the cosine function is set to 1.0. This works well in the upper, as well as in the lower, panel of Figure 18, because all attributes were measured on the same kind of (100-mm visual analogue) scale (see the upper panel of Figure 17). The deviations of the data points from the estimated values, represented by the cosine curve in Figure 18, correspond to the communalities of the attribute vectors in the first two principal components of Figure 6. However, these values are not identical to the communalities, because the values plotted in Figure 18 are actual regression or correlation coefficients, not the principal-component loadings presented in Figure 6.

According to the Information-Load Model, this interconnectedness of attribute scales of perceived affective and conceptual quality results from Information Load. As presented in Chapter 5, entities low in degree of information load are boring, at some higher degree of information load entities are pleasant, at above moderate degree of information load entities are interesting, and when exceeding the individual’s processing capacity, at extremely high degree of information load, entities are unpleasant (cf. Figure 3). This relationship between Information Load and perceived affective and conceptual qualities of stimuli causes the corresponding attribute scales to correlate, and to be organised in a meaningful circular order that represents increasing degree of information load (see Figures 5–7, and Figure 18).
7.6. The Information-Load Model applies beyond the present sets of data

Two final questions to address are: (1) to what extent may my results be generalised beyond the present sets of data, and (2) what are the limitations of my research? My experiments (Papers I–III) possess two major strengths. First, they are based on large and comprehensive sets of samples in terms of participants, stimuli and attribute scales. This would support the stability, representativeness and possibility to generalise my results, predominantly, within the domains of photographs and soundscapes. In addition, the fact that my results find strong theoretical and empirical support in previous research, on for example problem solving (Eckblad, 1981b) and perception of places (e.g., Russell, Ward & Pratt, 1981), provide support to the possibility to apply my results beyond the present sets of data, in terms of stimuli. Moreover, the fact that preferences to photographs depended on Information Load both for people with a high (photo professionals) and a low (psychology undergraduates) capacity to process photographic information provide support to the possibility to apply my results beyond the present sets of data, in terms of people. I assume that capacity to process information is the most important individual factor to aesthetic appreciation and that other factors, such as gender, age, or socio-economic class, are more or less irrelevant.

Second, my use of (1) real experts in the form of photo professionals, (2) compound entities like photographs and soundcape excerpts, as well as, (3) attribute scales empirically grounded in perceived aesthetic appreciation, would support the validity of my results. In contrast, researchers in psychological aesthetics typically study expertise by recruiting a group of undergraduate students, randomise the sample into two groups, provide one of the groups with training, and appoint this group as experts (see e.g., Silvia, 2006a). In regard to stimuli, early research in psychological aesthetics often used polygons or random sequences of pure tones (see e.g., Berlyne, 1974). As I report in Section 2.2, on the Preference-for-Prototypes Model, present research on psychological aesthetics more often use real-life objects, like reproductions of paintings, as stimuli. In regard to attribute scales, these are still most often based on theoretical assumptions or adapted from previous research [see e.g., Berlyne (1971), and my critique of the research on the Preference-for Prototypes Model]. In this way the researcher risks to miss factors that are important to aesthetic appreciation.

Limitations of my research are chiefly related to practical constraints, such as limited resources and physical restrictions, as well as, the exploratory nature of my research. For example, I mainly used university students, which limits the external validity of my experiments. However, with the purpose to reduce the risk of bias, I have not only recruited psychology undergraduates but students from various universities and academic faculties. The use of psychology undergraduates in Experiment 1 of Paper I, on Multidimensional Scaling, is probably not a problem. Multidimensional Scaling analysis assumes
that there are common sources of variation in responses to stimuli among individuals. Therefore, it is predominantly the size of the group of participants that is most important in this qualitative analysis (see Paper I for a detailed discussion). Paper III confirms that there is sufficient variation also in a small group of 10 psychology undergraduates—without aesthetic training—in regard of preferences to photographs in order to map the relevant dimensions (see Figure 3 of Paper III).

The exploratory nature of my research means that I originally did not know what factors would turn out to be important to my results. Today I know that I may vary the stimulus samples more systematically. For example, soundscapes contain sounds of humans, nature and technology. It would be interesting to conduct an experiment based on a complete factorial stimulus design on absence/presence of these properties, in the way I created the 32 photographs used in Paper III. In addition, I have demonstrated that photo professionals are different from psychology undergraduates and that this difference is essential in regard of preferences to photographs. Future research in psychological aesthetics must aptly take this into account.

7.7. The Information-Load Model creates new research prospects

The Information-Load Model creates new prospects for research in psychological aesthetics. Besides subjecting the Information-Load Model to further scrutiny, researchers may explore what factors, like stimulus properties and psychological factors, contribute to the degree of information load. Results in this area would provide a better understanding of how to design compound entities from an aesthetic point of view. For example: (1) how may the composition of sound categories, or the temporal occurrence of sounds, contribute to the degree of information load of soundscapes?; (2) how does motifs, view angle, composition, picture format, dept of field, degree of zoom, lighting, visual contrast, degree of colour saturation, motion blur, and so forth, contribute to the degree of information load of photographs?; (3) how does education, or professional experience, contribute to the capacity to process information?; (4) what other factors may facilitate or impede information processing and thereby contribute to the degree of information load?

In order to accelerate progress in psychological aesthetics it is central that researchers agree on the dependent variable, on how it should be operationalised and measured. It is not constructive to continue to use different dependent variables, or variables that are assumed to measure aesthetic appreciation, for example, Like–Dislike, Attractive–Unattractive, and Beautiful–Ugly. These variables are frequently used as substitutes for Preference, and are clearly influenced by Hedonic Tone. Lack of consensus in respect to the dependent variable can only lead to confusion and results that cannot be compared across studies.

Summary and Conclusions

Information Load is the key factor underlying aesthetic appreciation. When 34 psychology undergraduates were asked what qualities they perceived in 564 photographs, in regard to aesthetic appeal, they produced a set of 189 attributes that correspond to different degrees of information load. Applied in Principal Components Analyses, to photographs and soundscape excerpts, improved sets of these attributes were organised in a predicted, meaningful order that represent increasing degree of information load. Between the attribute vectors ‘Unpleasant’ and ‘Boring’, which represent the two endpoints of the underlying information-load dimension, a predicted gap devoid of data points was revealed in the component-score plots. Inspection of photographs organised along the information-load dimensions demonstrated that Information Load is more than a theoretical construct—it represents something real. Neither is Information Load an artefact caused by the Principal Components Analysis. A Multidimensional Scaling analysis revealed an almost identical data configuration in two dimensions, representing Information Load.

The main conclusions of the present doctoral thesis are:

(1) An Information-Load Model is proposed, which incorporates the five general components Aesthetic Appreciation, Hedonic Tone, Expressiveness, Familiarity, and Uncertainty. The relationships between these five components may be illustrated as a vector representation (Figure 3).

(2) Information Load is the key factor underlying aesthetic appreciation. It is a higher-order latent factor that, hypothetically, results from resistance caused by information processing. Presumably, the degree of information load increases with the amount of information of stimuli and decreases with peoples’ capacity to process information.

(3) A Principal Components Analysis of the measures of a set of stimuli, varying in degree of information load, on the attribute scales Inexpressive–Expressive, Familiar–Unfamiliar, Pleasant–Unpleasant, Aesthetic–Unaesthetic, and Certain–Uncertain would reproduce Information Load as an information-load dimension, represented as a circular curve around the origin of the component-score plot of the first two principal components, along which the stimuli would be located in the order of their degree of information load (see Figure 3).
The degree of information load of stimuli is measured as the angular distance in arc-degrees (i.e., 0°–360°) along the information-load dimension in the component-score plot. Low degree of information load corresponds to ‘Inexpressive’ and high degree of information load to ‘Unpleasant’. A sector in the component-score plot between the positions of these two attribute vectors would be devoid of data points. This indicates where the information-load dimension begins and ends.

Individuals give different weights to the general components included in the Information-Load Model. For example, photo professionals preferred photographs they perceived as uncertain and expressive, largely ignoring Familiarity and Hedonic Tone. Conversely, psychology undergraduates, with no aesthetic training, preferred photographs they perceived as familiar and pleasant, largely ignoring Uncertainty and Expressiveness.

Responses to soundscapes largely resembled the photo professionals’ response pattern to photographs, that is, Familiarity was ignored. Within the present theoretic framework this means that the participants in Paper II had the required capacity to process all soundscapes presented.

Thus, aesthetic appreciation corresponds to an optimal degree of information load, or represents an ideal point on the information-load dimension. As an individual learns to master information in a particular domain (e.g., photography or soundscape) the optimal degree of information load, which corresponds to aesthetic appreciation, increases.

Acknowledgements

An adventure has met its objective. For many years I have contemplated what factors determine aesthetic appreciation, a journey that began with the need of a photography student to understand what makes an amazing photograph exactly that. When no one seemed to know the answer I decided to seek it on my own. The journey has been tough and lined with obstacles, of which financing proved to be only one. Still, I would not have approached this challenge differently, if possible.

Guided by Verner von Heidenstam’s wisdom “sweeter listening to a string that broke than never to draw a bow” I wandered deeply into my mind. All more frequently I thought I could see the light in the end of the tunnel, only to realise it was oncoming traffic, a dead-end or the wrong exit. The answer, seemingly close, continued to elude me. Gradually I learned that scientific research is not simply a matter of collecting empirical facts. Facts may not necessarily speak for themselves, they need a solid theoretic framework in order to make sense. In the present doctoral thesis I have shared with you my conclusions. I have entitled my doctoral thesis “Aesthetic Appreciation Explicated” confident that I am on to the truth.

I am grateful to many persons who have supported me on my journey through life, thus far: my parents Curt and Anna-Lena Axelsson who gave me life and the opportunity to explore this world; my uncle Arnold Bernström who was the first to understand my reading and writing difficulties, popularly known as Dyslexia. Without his help to understand the severe learning difficulties I experienced in elementary school, such as learning English, I would probably never had the courage or self-confidence to apply to university in the first place, even less to believe that I could perform a miracle. I am grateful to my colleagues and mentors at the Department of Psychology, Stockholm University: Professor Åke Hellström who brought me into the PhD program; my thesis advisers Associate Professor Mats E. Nilsson and Professor Birgitta Berglund whose patience I repeatedly have tested over an extended number of years. I am also deeply grateful to Stockholm University that provided me the chance to prove my capacity, and to the Swedish education system that creates opportunities also for the apparently weak. Special thanks go to Professor Lars R. Bergman, Professor Tommy Gärling, and Professor Maria Larsson for valuable comments on the text.

This research was sponsored by grants to Professor Birgitta Berglund and/ or Associate Professor Mats E. Nilsson from the Swedish Foundation for Strategic Environmental Research (MISTRA), the EU FP5 RANCH Project,
the Swedish Research Council for Environment, Agricultural Science, and Spatial Planning (Formas), the Swedish Research Council (VR), and by grants to the author from the Department of Psychology, Stockholm University. I also acknowledge travelling stipends from the Wallenberg Jubilee Fund, and the Division of Perception and Psychophysics at the Departmental Psychology, Stockholm University.

References


