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Assessing the visual complexity of urban form: A typology of measures and indicators

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Abstract

Visual complexity, alongside other forms of complexity in cities, serves as a daily stimulus in the perception of urban environments. Various studies have addressed optimal visual complexity and the organization of environmental data, considering the limited processing capacity of the human brain. Despite significant prior research, the challenges of quantifying visual complexity, the scarcity of indicators that predict perceptual complexity, and the dispersion of existing indicators across multiple disciplines have resulted in a lack of clarity and validity in this field. This study aims to establish a precise definition of complexity, particularly visual complexity, in relation to the physical structure of cities, and to present a comprehensive classification of visual complexity indicators applicable to urban design scales. To achieve this, the study reviews related literature from the fields of aesthetics, environmental psychology, architecture, and urban design to identify the factors influencing the visual complexity of urban forms. Additionally, a typology of methods for measuring visual complexity is presented in a table, categorized into two main groups: the first group includes methods that use urban landscape elements as units of complexity measurement, while the second group comprises methods that consider the informational units received from the visual environment as the measurement units. Given the importance of assessment scale in measuring complexity, a six-level hierarchy for evaluating indicators is proposed. This table serves as a comprehensive summary, potentially functioning as an effective tool for analyzing and determining the optimal level of visual complexity in relation to urban form. It can help prevent confusion in studies related to environmental complexity. Furthermore, the study highlights the importance of movement in the perception of complexity, the role of attention, the impact of semantic dimensions, and familiarity with the environment as factors that distinguish urban complexity studies from those in other fields.

Keywords: Visual complexity; Environmental perception; Urban form, Visual information; Information theory; Complexity measurement

1. Introduction

In contemporary cities, citizens face two contrasting challenges: on one hand, they are confronted with visual clutter and perceptual overload caused by disorganized complexity; on the other hand, they encounter monotonous environments that, due to the lack of essential visual data acting as reference points, make the reading and memorization of urban forms difficult. Human short-term memory has limited information processing capacity (Portugali & Stolk, 2016: 9), and as a result, the human brain has evolved to manage environmental complexity by organizing it in a way that reduces the raw information needed to identify an object or system (Salingaros, 2010:3). Complexity is closely linked to human physiology and can trigger a range of anxiety-related responses, such as increased heart rate and sweating (Session & Salingaros, 2010: 3). Functionally, undesirable complexity also has adverse effects. Environments that are either too monotonous or excessively complex without organizing patterns are not easily understandable or memorable, leading to confusion (Vandenberg et al., 2017: 3) and impairments in cognitive-functional processes such as wayfinding and the formation of cognitive map.

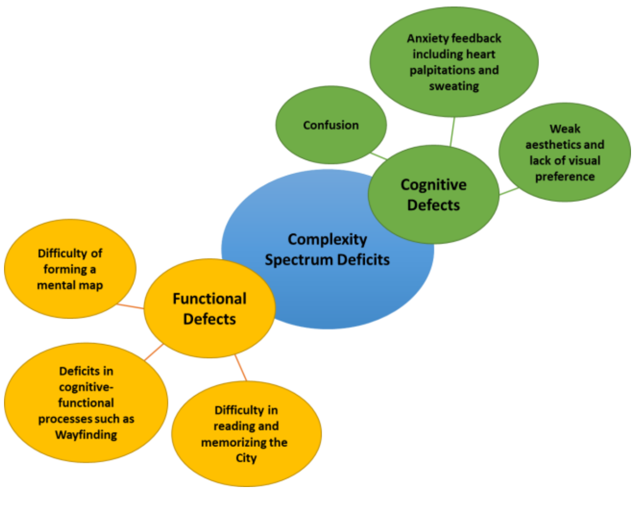

Fig. 1. Functional and cognitive impairments at both ends of the complexity spectrum

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2. Defining the Concept of Complexity in the Urban Context

Multiple definitions of complexity have been proposed by researchers in the field of urban studies. According to Batty (2005), " The term complexity refers to the higher-order phenomena arising from a system's many connected, interacting subcomponents and describes both dynamics (i.e., processes) and structure (i.e., patterns and configurations)" (Boeing,2018:2). From a systems perspective, Salingaros defines complexity as the property of a system that makes its use, understanding, management, or implementation difficult, and is considered a measurable feature. Complexity indicates the presence of details in the structure, stored information about how the system operates, and its arrangement (Salingaros, 2014: 7-18). Arnheim (1968), in his book "Order and Complexity in Landscape Design," defines complexity as: " Complexity is the multiplicity of the relationships amongst the parts of an entity. " (Heath et al., 2000: 207). In contrast, Berlyne's (1971) definition posits that: A pattern is considered more complex, the larger the number of independently selected elements it contains. In two patterns that consist of the same number of elements, that one will be less complex that has a greater degree of similarity among its elements or, more generally, a greater degree of redundancy of interdependence (Heath et al., 2000: 207). Conversely, Kaplan et al. (1982) consider such quantitative definitions of complexity to be incorrect. They prefer terms like richness or diversity. Complexity "reflects how much is going on" and how much attention is required (Kaplan, 1979: 243). Recent studies by researchers such as Van Geert and Wagemans (2018) define (stimulus) complexity as those aspects related to the quantity and variety of information (in a stimulus) (Van Geert & Wagemans, 2018: 3). Broadly, these definitions share two fundamental aspects: the presence of multiple elements and the interactions between these elements. In this study, complexity refers to "a measurable feature of a system composed of a set of interacting elements that makes the perception of the system difficult."

3. Visual Complexity Perception of Urban Form

Humans perceive complexity, like other environmental stimuli, through their five senses; however, most studies on complexity in urban spaces have focused on the visual perception of complexity. Research has shown that, with few exceptions, the visual sense dominates and prevails over other senses when there is a conflict among sensory inputs (Rapoport & Kantor, 1967: 214). As a result, in environmental perception studies, due to the dominance of visual information over other senses, there has been a focus on how visual complexity is perceived.

Despite extensive research on visual complexity, there is a notable gap in understanding the perception of visual complexity of urban form. Extensive studies on the "optimal level of complexity," where perception, mental representation, and recall of visual data occur more easily and quickly, have been conducted in various research fields, particularly environmental psychology, under the term "good visual complexity" with the aim of finding a balance between order and disorder or " Unity in variety" (Elsheshtawy, 1997; Boeing, 2018: 7; Ewing & Handy, 2009). These studies, which will be reviewed later in this paper, generally seek to establish a correlation between brain mechanisms' efficiency and a moderate level of environmental complexity (Portugali & Stolk, 2016: 9; Portella, 2016: 26). However, noteworthy studies in this area have primarily addressed visual complexity from a perceptual and emotional sensory perspective, rather than exploring how varying levels of complexity affect the ease of perception, memorization, and mental retention of visual data from a functional standpoint. Additionally, these studies often focus on abstract variables (such as basic geometric and simple shapes) and less on actual visual data. Consequently, how and which aspects of the visual environment of urban forms affect the perception of visual complexity remains unclear (Hussein, 2018:5). Another reason for the lack of studies on visual complexity of urban forms is the difficulty in defining objective complexity, especially in the third dimension, and measuring perceived mental complexity. Objective complexity refers to the amount or degree of complexity physically present in a specific stimulus, in contrast to Subjective complexity, which involves the participants' perception of the stimulus's complexity (Van Geert & Wagemans, 2018: 4). Empirical evidence suggests that in simpler cases, a good correlation can be found between judged complexity and quantitative aspects of stimuli (Heath et al., 2000: 207). However, for more complex cases, such as urban form, more detailed studies are needed. As a result, there is currently little agreement on how to define and measure complexity, leading to limitations and ambiguities in studies in this field (Hussein, 2018: 11). The following sections will briefly introduce studies on optimal visual complexity in the fields of aesthetics, psychology, architecture, and urban planning, and evaluate them from the perspective of visual complexity in urban forms.

3.1. Optimum visual complexity

3.1.1. Aesthetics and environmental psychology

Visual complexity concept, holds considerable potential to connect different disciplines. Many studies in this area have focused on the processes of perceiving complexity in relation to experimental aesthetics and Gestalt psychology, and have subsequently been explored in architecture and urban planning.

Historically, many philosophers have suggested the importance of a proper balance between order (unity, uniformity, composition, harmony, regularity, and organization) and complexity (variety or multiplicity) to explain aesthetic value (Van Geert & Wagemans, 2018: 18). It was Fechner (1876) who introduced a shift from more deductive and theoretical methods to inductive and empirical approaches in aesthetics. He proposed the aesthetic principle of the mean, which posits that stimuli experienced as pleasant should have a sufficient balance between order and complexity, with individuals being able to tolerate a moderate level of arousal for longer periods compared to very low or very high levels, which respectively cause under- or over-stimulation (Van Geert & Wagemans, 2018: 19). Later, Birkhoff (1933), a mathematician, also measured aesthetic quality in his book "Aesthetic Measure " According to him, aesthetic quality (M) depends on two factors: order (O) and complexity ©. Eysenck (1942), a psychologist, refined Birkhoff's work by proposing a formula as a multiple of order and complexity to measure beauty. Following these studies, a series of investigations aimed at achieving aesthetic satisfaction identified a moderate level of complexity as a key variable. Berlyne (1960) introduced the variables of novelty, incongruity, and complexity in his book " Conflict, Arousal, and Curiosity." According to his studies, these variables induce arousal in the human mind, leading to aesthetic satisfaction. Berlyne's model predicts that people generally prefer stimuli with moderate complexity over very simple or highly complex ones. According to this theory, the relationship between complexity, arousal, and preference should be an inverted "U" shape: " Moderate arousal potential will be maximally rewarding" (Berlyne, 1960: 201). Arnheim (1966) proposed a contrary yet complementary relationship between the two concepts. Specifically, he stated that although order tends to reduce complexity and complexity tends to reduce order, both order and complexity are mutually required: "Complexity without order produces confusion. Order without complexity produces boredom" (Arnheim, 1966: 124). Aligning with Berlyne's studies, Stroffert and Skrudral (1965) identified a common visual preference among humans, despite minor individual differences. Their experiments found that the common point was a preference for "bits" of information in each unit of time.

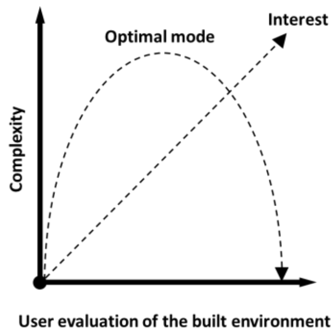

Fig 2. The relationship between user enjoyment and interest in the built environment relative to the level of complexity
(Source: Berlyne, 1960: 201).

Rachel and Stephen Kaplan (1976) identified the negative consequences of environments that are perceived as either too complex or too uniform for user behavior. These include difficulties in navigation due to excessive or insufficient visual stimuli and a lack of interest. They also demonstrated that complex scenes are generally evaluated more positively than simple ones, as they provide more information. When an environment presents either excessive or insufficient information, individuals may experience confusion or boredom and may avoid that particular environment. Thus, overall, psychological studies on visual complexity suggest that most individuals prefer a moderate level of stimuli.

Preferences for complexity are directly related to basic and physiological needs. Berlyne (1960) reported that when infants aged three to nine months were given a choice between three patterns ranging from simple to complex, their visual attention was drawn to the most complex pattern (Rapoport & Kantor, 1967: 212-213). However, this preference for complexity is not without limits. Extremely simple stimuli lead to rapid boredom, while overly complex stimuli can cause confusion and avoidance of perception. McReynolds (1960) and Kessen and Monsinger (1964) noted that individuals prefer only a specific degree of perceptual input—one that they can handle. This suggests that the optimal perceptual rate can vary for each individual (Rapoport & Kantor, 1967: 214). Extremes of complexity (both low and high) are not positively evaluated by observers (Portella, 2016: 25-26), and there is always an ideal level of perception.

Hebb (1949) provided a neurological explanation as a possible basis for the idea that optimal preference lies in a moderate range of arousal stimuli (Rapoport & Kantor, 1967: 215). Thus, in relation to user perception and evaluation, there is a connection between emotional aspects of pleasure and interest with complexity. Regarding the dimension of "pleasure," this relationship is direct up to an optimal level, beyond which it becomes inverse. Despite extensive efforts to define this optimal level, the number of factors influencing user perception and evaluation of physical environment is such that no clear definition can be provided (Portella, 2016: 26), leaving the optimal level still somewhat ambiguous.

In environmental psychology, complexity has been examined as a factor for landscape preference. Complexity indicators developed within the framework of landscape ecology can be applied to obtain relevant information about the complexity of a landscape from visual experience. However, research indicates that the theoretical basis connecting existing indicators with people's landscape experiences is weak. This has slowed the development and application of visual quality indicators and user experiences (Asa et al., 2010: 111-112). This issue arises because existing theories on perception in environmental psychology are generally based on abstract stimuli or extreme examples (e.g., urban vs. rural). Additionally, landscape aesthetics theory often lacks a quantitative basis to link its concepts to human responses for urban landscape metrics. These metrics are frequently used to describe perceptual visual qualities of landscapes to achieve some consistency, but only to the extent that they have broad positive or negative consequences for preference (Asa et al., 2010: 112). Most psychological or environmental psychology work on complexity deals with the number (richness) and/or variety (arrangement) of elements to be observed (Asa et al., 2010: 114). However, in more recent studies, many psychologists have focused on measuring only complexity, rather than the broader concept of "aesthetic quality." These efforts primarily measure abstract forms through counting lines, intersections, and internal angles. Such measures are unsuitable for buildings and street scenes, as building facades do not consist of separate pieces but rather of various elements that interact in complex ways (Elsheshtawy,1997: 303). Therefore, despite valuable foundations, defining, quantifying, and measuring the visual complexity of urban form remains significantly ambiguous, limiting research in this area.

3.1.2. Architecture and urban design studies

The concept of visual complexity, specifically its perception in urban spaces, has long been addressed intuitively. For example, Cullen (1961) emphasized the need to enhance differences between places to amplify sensory effects and harmonize them, rather than reducing them to uniformity (Rapoport & Kantor, 1967: 219). However, it was modern architecture and urban design that formally addressed complexity as an issue. Robert Venturi (1966), in his book Complexity and Contradiction in Architecture, was one of the first architects of the century to explicitly call for greater complexity in architecture. He criticized modernist ideas that led to creating a monotonous and boring environment. Venturi rejected the famous saying "less is more" and proposed that "Less is a bore" (Venturi, 1966). This implies that removing decorations or complexities leads to dullness (Elsheshtawy, 1997: 302). Consequently, visual complexity in architecture and urban planning gained increased attention as a counterpoint to the criticisms of modernist architecture and urbanism, as excessive simplification ignored human psychological needs for visual interest (Mims, 2005: 50).
Despite the limitations of existing studies, several efforts have been made to provide a framework for studying urban form perception, including examining environmental complexity. These efforts have led to the development of models for assessing visual complexity in urban forms. Rapoport and Kantor (1967) explored the concept of "Ambiguity" or complexity as an optimal state, discussing a spectrum from uniformity to chaos as perceptual deprivation and sensory overload. Uniformity and chaos create similar effects, and Rapoport introduces the notion of "optimal perceptual rate" in relation to the concept of ambiguity in physical environmental complexities.

Fig. 3. Different levels of visual complexity in urban spaces

The concept of "pattern" was introduced by Christopher Alexander in his book A Pattern Language (1977). Each "pattern" signifies a rule governing a part of a complex system. We observe our surroundings and learn its structure by abstracting cause and effect and recording recurring solutions in different conditions. These experiential rules, representing orderly behavior, are called patterns. Simple visual patterns are the most basic form of the concept of a pattern. In his later book, The Timeless Way of Building (1979), Alexander introduced the concept of " The quality without name" and ultimately presented patterns that, while simple, can be combined to achieve the complexity Alexander sought. This complexity is organized according to rules for achieving the quality without name. Alexander, after 30 years of deep study, published The Nature of Order (2002, 2004). In this book, he introduces the concepts of integrated wholeness and centers, describing the edge of chaos —a balanced place between order and chaos or between simplicity and complexity. Alexander's "Well-organized complexity" is what Weaver and Jacobs termed "Organized complexity." In The Nature of Order, Alexander proposes fifteen essential features to illustrate how centers enhance one another: Levels of scale- Strong centers- Boundaries - Alternating repetition- Positive space- Good shape- Local symmetries- Deep interlock and ambiguity- Contrast- Gradients- Roughness- Echoes- The void- Simplicity and inner calm - Non-separateness.
Lozano (1988) emphasized the need for diversity, variety, and rhythm in sensory variables and proposed two hypotheses. The first hypothesis states that humans require a combination of various visual inputs from the environment. The second hypothesis posits that these different visual inputs are not contradictory or exclusive but rather complementary and should be combined in an environment. The absence of a particular type of visual input negates the effects of other visual inputs. Lozano refers not to a spectrum of complexity but to a mix of different complexities, both high and low, suggesting an alternative concept of optimal complexity that exists within a moderate range of complexity.
Salingaros (2014) introduces two distinct types of complexity: Disorganized and Organized. Both require a high number of words but have distinct underlying mathematical structures. Structured complexity avoids information overload.

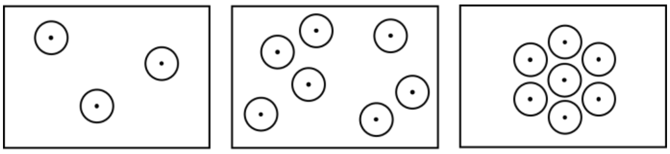

Fig. 4. Types of complexity from salingaros point of view left: simplicity, middle: disorganized complexity, write: organized complexity (Source: Salingaros, 2014:19)

According to Salingaros, the human cognitive system can only perceive complexity if it is somehow organized. He refers to ancient methods that have historically been used in human artifacts to organize environments. These methods include continuity, various forms of symmetry, scale, coherence, and coordination. Salingaros views these organizational methods as aligning with the complexity present in nature and living organisms. With an evolutionary approach, he argues that the human perceptual system is attuned to organized complexity due to its evolution in natural environments and is mismatched with unstructured complexity.
Salingaros then proposes a framework that he believes enables the creation of organized complexity. The

organizing features he identifies as tools for structuring complexity include: Linear continuity among different pieces, Different symmetries on the same scale, and Scaling symmetry (Salingaros, 2014: 19).

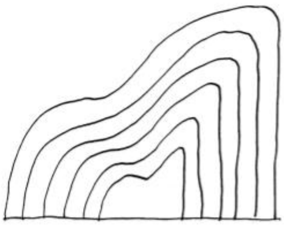

Fig. 5. Symmetry with scale connects similar shapes in different sizes (Source: Salingaros, 2014:19).

Jack Nasar (1987) conducted three studies examining the impact of complexity and coherence on the visual quality of street scenes in commercial areas. For these studies, shoppers and sellers were asked to review color photographs of nine simulated street scenes, each with varying levels of complexity (diversity in size, shape, and color in signs and letters) and coherence (size and contrast in signs and letters). Responses indicated that comfort was highest with moderate complexity and high coherence.
Overall, these researchers, despite their diverse literature, have pointed to a spectrum of complexity in urban environments. Table 1 summarizes the key works of scholars in architecture and urban studies, along with their definitions of complexity.

Table 1
Summary of Scholars' Works on the Spectrum of Urban Form Complexity

Scholar	Name of Work	Spectrum of Complexity
Rapoport & Kantor	Complexity and Ambiguity in Environmental Design (1960)	Monotony, Ambiguity, Chaos
Jacobs	Death and Life of Great American Cities (1961)	Monotony, Disorganized complexity, Chaos, Organized Complexity
Alexander	The Pattern Language (1977), The Timeless Way of Building (1979), The Nature of Order (2002, 2004)	Chaos/ Disorder, Well-Organized Complexity (or edge of chaos), Simple Order, Order
Lozano	Visual Needs in Urban Environment and Physical Planning (1988)	Very low (simplistic) order, Very high (complex) order, Presence of both types of visual input
Salingaros	Complexity in Architecture and Design (2014)	Disorganized Complexity, Organized Complexity
Nasar	Effects of Complexity and Coherence of Landscape on Visual Perception from Commercial Passages (1987)	Simplicity, Moderate complexity, High Complexity

A common thread among these studies is the presence of a spectrum of complexity ranging from low to high, as well as an optimal moderate level of complexity. Studies also show that user preferences are related to this optimal level of complexity. The initial assumption of these studies is that cities should possess a moderate level of complexity and evoke sensory stimulation through "unity in variety" (Elsheshtawy, 1997:302). It seems that optimal stimulation for cognition depends on experiencing environments that are adequately stimulating yet not excessively challenging. Environmental complexity plays a crucial role in determining whether an environment provides such optimal stimulation (Cassarino & Setti, 2016:1).

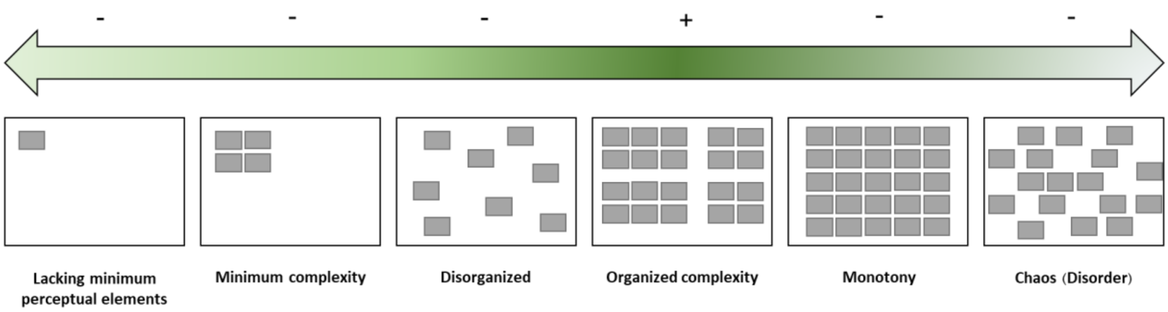

Fig. 6. Representation of the complexity spectrum, from excessive simplicity (lacking minimal perceptual elements) to chaos (disorder).

3.2. Factors and characteristics of urban form visual complexity

Visual complexity in urban form is influenced by various factors, some of which are constantly changing. These include individual characteristics and environmental features, which encompass both physical (static) and non-physical (dynamic) components. Physical components are influenced by two main groups of variables: visual and structural. Non-physical characteristics are subject to ongoing change. The factors affecting visual complexity in urban form, as identified in various refferences, are summarized in the table 2.

Table 2
Components affecting the visual complexity of the urban environment based on previous studies

<table>
<tr><th colspan="4">Factors Influencing Visual Complexity in Urban Morphology</th><th>Reference</th></tr>
<tr><td rowspan="7">Individual characteristics</td><td colspan="3">The mental state or instant motivation of a person affects reception and utilization of information provided by the environment. For instance: hunger increases the significance of a restaurant.</td><td>Rapoport & Hawkes, 1970:107</td></tr>
<tr><td colspan="3">More sophisticated observers, through training and exposure, tend to prefer greater complexity. Exposure to richer environments enhances the brain's capacity for information processing, thereby increasing the preference for greater complexity.</td><td>Rapoport & Kantor ,1967:214</td></tr>
<tr><td colspan="3">Ethnicity and Culture related learned experiences affects the processing and memory of design features.</td><td>Julian,2010:31-32; Portella ,2016:26; Elsheshtawy, 1997:314</td></tr>
<tr><td colspan="3">The factor of familiarity significantly influences the perceived complexity of an environment. Unfamiliar and familiar environments impose distinct cognitive loads on individuals. As familiarity with an environment increases, the importance of the complexity of its layout diminishes.</td><td>Phillips, 2015:18; O'Neill,1992; Donderi,2006:94; Streufert & Schroederal, 1965</td></tr>
<tr><td colspan="3">Cognitive style is consistent inter-individual difference in ways people acquire, organize and process information. It includes two main classifications: visual-verbal cognitive styles and object, spatial, and verbal cognitive styles.</td><td>Ugwitz- 2017:21</td></tr>
<tr><td colspan="3">Age influences individuals' cognitive abilities, including memory, attention span and processing speed.</td><td>Julian, 2010</td></tr>
<tr><td colspan="3">Gender related learned experiences may affect the processing and memory of design features. For example, the use of different navigation strategies among men and women.</td><td>Julian,2010:31-32</td></tr>
<tr><td rowspan="7">Environmental features</td><td rowspan="3">N non-physical (dynamic) components</td><td>Ecological</td><td>Sun light and vegetation enhance environmental complexity by adding details and rich textures to urban areas.</td><td>Ewing & Handy, 2009:80; Elsheshtawy, 1997:314</td></tr>
<tr><td>Social</td><td>The number of individuals present in an environment.

Activities taking place within the urban environment</td><td>Elsheshtawy, 1997:314;Ewing & Handy, 2009:81; Rapoport & Hawkes, 1970:110;</td></tr>
<tr><td>Transp ortation</td><td>Number of vehicles</td><td>Seto,2008</td></tr>
<tr><td rowspan="4">physical (static) components</td><td rowspan="3">Visual variables</td><td>Architectural style and façade details encompass building materials, surface texture and color, the skyline, building lines, street edge lines, rhythm, and modularity of the façade, particularly the numerous number of doors and windows.</td><td>.(Ewing & Handy, 2009:80 ;Rapoport & Hawkes, 1970:110; Elsheshtawy, 1997:314</td></tr>
<tr><td>Width of buildings: narrow buildings in varying arrangements add to complexity, while wide buildings subtract.

Diversity of the Spatial Envelopes of Buildings</td><td>Ewing & Handy, 2009:80</td></tr>
<tr><td>Urban furniture, commercial signage, and wayfinding signs, especially in urban commercial areas.</td><td>Ewing & Handy, 2009:80-81; Portella, 2016: 26; Cullen: 1961; Portella b, 2016:1</td></tr>
<tr><td>Structural variables</td><td>Structural variables influence the perception of visual complexity in urban spaces through movement. The greater the number of changes within the field of view, the more information is available. Directional changes with sharper angles are more noticeable.</td><td>Rapoport & Hawkes, 1970:109</td></tr>
</table>

It is important to note that individuals living in different locations may perceive and accept changes in the physical characteristics of street scenes at varying levels (Portella, 2016, pp. 25-26). Additionally, a physical pattern may present varying degrees of complexity to different individuals, yet correlations among these perceptions will likely exist (Elsheshtawy, 1997: 303). While each person lives within their unique world, similarities in social life, past experiences, and the current urban environment lead to shared perceptions of the environment among large groups of people (Knox & Pinch, 2000: 295; Carmona et al, 2003). Therefore, it can be concluded that in spatial design, an optimal level of perceptual complexity can be considered for the general public.

In advancing studies related to the urban environment, it is crucial to focus on the specific characteristics of visual complexity perception associated with urban spaces, distinguishing these studies from other approaches, such as environmental psychology. As mentioned earlier, the perceived complexity by citizens is influenced by individual characteristics and environmental features. Each of these contributing factors requires careful consideration during research and must be controlled during data collection and analysis, if necessary.

- Movement in Urban Space:

A key factor differentiating the complexity of urban form from other visual complexity studies, such as aesthetic studies, is the impact of movement on the level of complexity (Rapoport & Kantor, 1967: 219). Although current morphological indicators are suitable for identifying the static or topological characteristics of a space, they often neglect human movement and changes in configuration during spatial navigation (Kwon, 2007: 160). It is essential to consider the relationship between complexity design and the speed of movement. For example, while walking at a slower pace, much more complexity is needed compared to the fast movement of a vehicle (Rapoport & Kantor, 1967: 216).

- Complexity and Attention:

Attention is a limited-capacity system that involves recognizing and orienting to sensory events for perception, processing, and maintaining alertness to stimuli (Phillips, 2015: 13). Eye-tracking studies have shown a correlation between the complexity of eye movement patterns and the complexity of the environment (Kochaki, 2017). In conditions of lower visual complexity, fixation rates decrease, which may simply be due to fewer stimuli in the environment (Phillips, 2015: 43).

- The Impact of Familiarity with the Environment on Complexity Perception:

Many studies have emphasized the relationship between novelty and perceived complexity (Elsheshtawy, 1997: 314). New and familiar environments can impose very different cognitive loads, likely related to the use of mental representations or cognitive maps (Phillips, 2015: 18). Although little difference was observed between new and familiar conditions in highly complex environments, a significant difference was found in low-complexity environments (Phillips, 2015: 40). Similar to the visual complexity of an environment, the level of familiarity can affect fixation behavior, indicating changes in attention allocation (Phillips, 2015: 85). As familiarity with the environment increases, the importance of complexity diminishes, leading to a reduction in perceived complexity (Demirbaş, 2001: 39).

-The Impact of Semantic Dimension on Complexity Perception:

A user's interpretation of the built environment depends on time, culture, and conditions. Together, these factors can determine the meanings associated with the physical characteristics of urban spaces (Portella, 2016: 36). Urban centers are recognized by the collective memory of people, which is linked to the symbolic meanings attributed to objects and places (Portella, 2016: 36). Numerous studies have highlighted the importance of meaning in perception as another significant component of environmental complexity (Rapoport & Hawkes, 1970; Demirbaş, 2001; Elsheshtawy, 1997). The semantic dimension is strongly influenced by cultural factors, which affect decisions about which aspects of a scene are highlighted and which are suppressed (Rapoport & Hawkes, 1970: 107). This makes the study of perceptual complexity in urban settings context-specific.

-Perception by the five senses

Despite the predominance of vision over other senses (Rapoport & Kantor ,1967:214), what makes the perception of environmental complexity in cities is a brain of environmental data collected by all senses, including hearing, smell and touch.

4. Measuring Visual Complexity in Urban Design

There is a significant connection between measuring complexity and the objectives of urban decision-makers, design, and planning interventions (Boeing, 2018: 3). However, the effort to measure complexity has consistently posed a challenge across various fields, from aesthetics to architecture and urban design, due to its inherently ambiguous nature. The vague definitions in classical foundations of this field do not provide the necessary tools to measure this variable in relation to other design variables, thereby necessitating further studies in this area.

Methods of measuring subjective visual complexity take into account the observer's perception of complexity but vary in the importance they place on individual differences. These methods either average the responses of participants or use individual scores from tests that involve selecting and ranking options based on perceived complexity (Van Geert & Wagemans, 2018: 6). In the context of street scenes, subjective complexity measurement is often conducted through ranking tests that assess the complexity perceived by participants.

Another segment of studies focuses on categorizing and identifying various factors influencing subjective complexity and on predicting perceived complexity based on objective complexity. For instance, Berlyne (1960) posits that subjective complexity of a stimulus is directly related to the number of distinguishable elements and the degree of dissimilarity among them. In another study by Berlyne et al. (1968), two primary factors determining subjective complexity were identified: (a) the number of selected independent component elements, which they termed the "information content" dimension, and (b) the "Unitariness vs. articulation" dimension in easily recognizable parts. This concept refers to the degree to which elements are perceived as indivisible units within a cluster versus a form of hierarchical organization where elements maintain important roles as natural parts of a larger whole (Van Geert & Wagemans, 2018: 6).

Nadal et al. (2010) distinguished between three different forms of visual complexity that affect individuals' perception of complexity: (a) the quantity and variety of elements, (b) the methods of organizing those elements, and

(c) their asymmetry (Van Geert & Wagemans, 2018: 10). Collectively, these studies highlight a major shortfall in objective indicators for assessing visual complexity, especially considering the geometric form characteristics of real environments.

Despite the extensive studies on measuring objective complexity to predict perceived complexity, few have examined the physical form's details, particularly from the perspective of a moving pedestrian. In this context, defining objective complexity indicators assists urban design theory and practice in critically evaluating and normatively balancing complexity goals based on local culture and policy (Boeing, 2018: 15). In a 2018 study by Boeing, methods of measuring complexity at the urban design scale were categorized into five groups: temporal, visual, spatial, scale, and connectivity (Boeing, 2018: 7).

The focus of current research is to examine and refine visual complexity indicators in urban design. In this article, complexity refers to the degree of visual stimulation in an environment and the details of those stimuli, which constitutes a key factor distinguishing different environments (Phillips, 2015: 19). In a simple urban scene, pedestrians perceive little new information from visual revelations at each step. In contrast, highly complex urban environments bombard individuals with a vast array of new information as they move through the space. In these examples, the space acts as the medium of the message, and the unfolding scenes themselves are the message. This message can be interpreted in arbitrary units such as meters or urban landscape units like street blocks or plots (Boeing, 2018: 7). Visual complexity metrics measure the amount of visual information a person receives while moving through an urban environment. Two important features must be considered when studying these indicators: first, the scale of assessment, and second, the components involved in the evaluation. Given the importance of scale in evaluating visual complexity, it is crucial to consider how the assessment scale applies to the complexity measurement indicators. Furthermore, due to the multitude of parameters involved in evaluating visual complexity, the number of components that each of these indicators accounts for in their calculation is also significant.

4.1. Types of components evaluated

Methods of measuring complexity in urban design studies can be divided into two major groups: studies that deconstruct the landscape into urban landscape elements and studies that evaluate the urban landscape as informational units. The following sections will examine visual complexity measurement methods using two approaches: the first method measures urban landscape elements as messages sent from the environment, and the second uses informational units as messages.

4.2. Scale of evaluation

According to Gibson's theory, human perception occurs through "orderly changes in a state" and "borders" which introduces a hierarchy of scales when considering complexity (Rapoport & Hawkes, 1970: 109). An element or pattern does not occur in isolation but is relative to its surrounding context. Norberg-Schulz (1965) argued that the distinction between elements and relationships is relative, and it is always possible to decompose an element into subordinate elements and relationships or to integrate elements and relationships into higher-level elements. In this way, a building as a whole within an urban context becomes an element. An element is always a whole at another level, which is itself composed of a set of elements (Elsheshtawy, 1997: 304). Scale should play a crucial role in developing morphological complexity metrics because it influences the amount of visual data received. Additionally, the scale of evaluation is particularly significant in relation to movement speed, as the speed affects the amount of data received per unit of time and, consequently, the perceived complexity (Rapoport & Hawkes, 1970: 109). In assessing pedestrians' perceptual complexity of urban facades, different scales of measurement can be applied to study the complexity of the facade. To analyze the scale at which each of the indicators measures visual complexity, it is essential to present a hierarchical model for analyzing visual complexity from the pedestrian’s viewpoint in the city.

Previous studies have also made proposals with this goal in mind. For example, Edward Hall (1959) offered that three types of components make up any message: isolates, sets, and patterns. The sets are perceived first; the isolates are the components that make up the sets, whereas the patterns are the way in which sets are combined together to have meaning. In urban environment this classification introduces these three levels: Level1-Buildings (set), Level2-Street-scene (pattern); Level3- Elements constituting a building such as the windows, cornices, etc (isolates). Complexity in this case is dependent upon the relationship between the various buildings constituting a street-scene, i.e. how much do they differ from one another. Additionally, Robinson (1908) proposed a quadruple classification: Level 1 – decorations (small-scale details; he believed this level is irrelevant for evaluating buildings at the urban design scale); Level 2 – horizontal and vertical differentiation expressed by openings; Level 3 – secondary volumes in elements like stairs, towers, windows, etc.; and Level 4 – overall volume, the primary compositional volumes of a facade. Another example is a quadruple classification proposed by Elsheshtawy (1997): Level 1 - Overall massing: This is articulated through the primary volumes of the façade composition. Level 2 - Secondary massing: Manifested in such elements as bays, stairs, towers, dormers, etc. Level 3 - Horizontal-vertical differentiation: Articulated by fenestration elements. Level 4 - Ornament: Manifested as small scale details (Level 1 through Level 3 were found to contribute to complexity at an urban design scale and relevant to the measurement of complexity).

Considering the objectives of this article, a proposed hierarchy for studying the visual complexity of streets is provided in Fi 7 which includes six levels and offers a more detailed hierarchy than the previous three classifications.

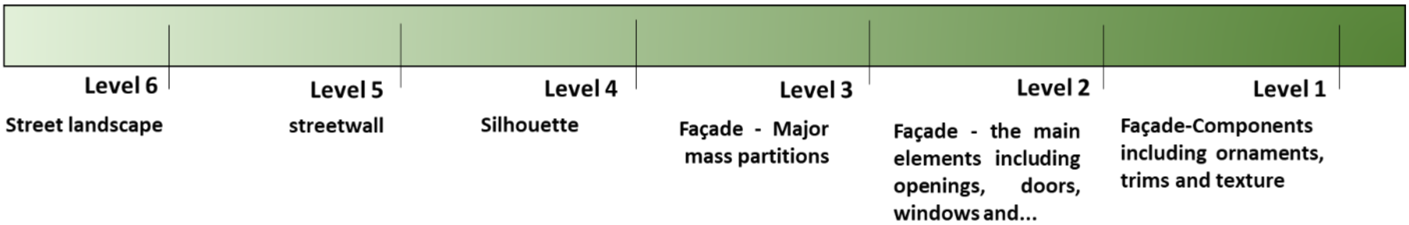

Fig. 7. Proposed Levels of Complexity

5. Measures of Visual Complexity in Urban Landscapes:

A systematic and cohesive classification of metrics and indicators for visual complexity in urban design studies is noticeably absent. This section categorizes and presents common visual indicators used to measure visual complexity in urban environments.

5.1. Methods *of assessing visual complexity based on urban landscape elements*

5.1.1 Krampen's types /tokens ratio

Krampen (1979) examined the relationship between subjective and objective measures of complexity. The subjective measures were semantic differential scales of complexity, while the three objective measures included the ratio of types to tokens. Six visual elements (sky, roof, wall, balcony, decoration, window display, door, or advertisement) were identified through an inspection of each façade. The second measure was the entropy of the facade. For this measurement, the facade was divided into a grid, and each cell of the grid was assigned to one of six categories. The third measure of entropy was based on the transitions between each cell in the grid. The underlying concept here is that large, homogeneous areas will be perceived as subjectively simple (Stamps, 1999:729).

5.1.2 Elsheshtawy method

In Elsheshtawy (1997) research, six visual elements were hypothesized for each building: overall massing, secondary volumes, openings, texture(s), width, and height. Complexity was calculated as the sum of the number of types of each element in the assembly (Stamps, 1999:729).

5.1.3 Stamps method

Stamps (1998b) reported on four factors: the number of vertices, symmetry, variation in the lengths of line segments, and variation in angle sizes (Stamps, 1999:730). His findings indicated that perceived complexity can be effectively predicted based on the number of rotations in the overall form outline. If the form is symmetrical, perceptions of complexity can be reduced by approximately 25%. About total mass of building, he reported three factors: whether a facade was divided into horizontal or vertical sections, the number of openings, and whether the volume was broken up (Stamps, 1999b:730). Any shape that exhibits bulges or indentations is concave (Stamps, 1999:730). The degree of concavity (the convex deficiency) can then be defined as the difference in area between a shape's convex hull and the area of the shape itself. The greater the protrusions, cutouts, or indentations, the larger the convex deficiency (Stamps, 1999:730). In a study Stamps (1999a) defined ambiguous term of "detail, using the visual perception theory proposed by Van der Laan (1983) (Stamps, 1999:732): Portions of the whole will have measurements ranging from 1 to 1/7 of the total. Ornamentation will have sizes between 1/7 and 1/49, while textures will consist of elements with lengths less than 1/49 of the total (Stamps, 1999:734). In the following Stamps (2000) classified façade details into three categories: Trim (such as door and window frames, and railings), Decorative ornaments (such as frames on base, body, and crowning of facades), and Texture created by facings (such as by stones or bricks) (Portella, 2016: 31).

5.1.4 Complexity method

(a) Silhouette: Refers to the peripheral shape of a building. When analyzing street walls, it encompasses the overall shape of all buildings contributing to the street view (Portella, 2016: 30). The silhouette's three physical characteristics that most affect complexity perception are: (1) the number of turns, (2) angular variation, and (3) symmetry. In commercial streets, variations in building height, width, and roof type (e.g., parapets, gables, sloped roofs) also impact user perception and complexity evaluation (Portella, 2016: 30).

(b) Façade Details: Portella and Stamps identified visual texture, primarily composed of small-scale details, materials, colors, and patterns, as the second significant aspect (Portella, 2016: 31). The concept of detail can be associated with the size, similarity, and proximity of smaller elements on a façade. Elements that are about one-seventh the size of the façade area are perceived as details. Even smaller elements can be recognized as details if they share similar shapes and are grouped together.

In terms of the perception and evaluation of the complexity of commercial signs, factors such as size, shape, proportions, arrangement on the façade, type of sign, placement on the façade, presence of images, font style, dominant letter style, letter size (height), number of color groups, color contrast between letters and background, and the separation of shape (letters or images) from the background based on size are crucial. Additionally, the number of signs, the percentage of the street façade covered by signs, and the sign area per square meter of the street contribute to increased complexity (Portella, 2016: 27).

(c) Façade Articulation: Facade articulation refers to saliencies and re-entrance on a physical volume or bulk (Portella, 2016: 32). Portella, citing Stamps' study, identified six additional physical aspects of building façades that can enhance user perception and assessment of articulation: vertical partitions, number of doors and windows, User's Perception and Cognition of the Built Environment 33 mass broken into smaller parts, reduced thickness of vertical elements, building proportion of width to height, and presence of trees in the foreground. (Portella, 2016, pp. 32-33). Additionally, variations in the shape and proportion of doors and windows can influence user perception of articulation.
Matin and colleagues, in their book "Urban Design: Decorations and Ornamentation," along with Portella's studies (2003), affirm that visual character and color variation are two other important features related to user perception and complexity evaluation in urban landscapes (Portella, 2014: 29).

(d) Visual Character: Visual character can be defined through the similarities between the physical characteristics of buildings within a street view. This perception depends on the frequency of façade design features. Visual character can be defined based on façade materials and a three-dimensional Euclidean space: (1) a defined area (block façade), (2) a set of design features (e.g., architectural style, number of floors, roof type, symmetry, etc.), and (3) the frequency of these features in the street view (Portella, 2016: 33).

(e) Color Variation: Color is the first aspect perceived by users in public spaces (Portella, 2016: 33). When analyzing color variations in commercial streets, color attributes such as hue, saturation, brightness, and color temperature should be considered (Portella, 2016: 35).

(f) Symbolic Meanings: Portella emphasizes the importance of symbolic meanings and addresses certain variables in the built environment that can carry these meanings, including building configuration, spatial configuration, materials, the nature of lighting, as well as non-visual elements like sounds and tactile and olfactory properties of surfaces and textures (Portella, 2016: 36). However, these topics are beyond the scope of the current paper.

5.1.5 Complexity Measurement Guidelines (Ewing et al.)

Ewing and his colleagues (2006, 2009, 2013) conducted a series of studies on the key perceptual features of urban environments (Ewing et al., 2006; Ewing & Handy, 2009; Ewing & Clemente, 2013). They aligned complexity with characteristics such as number of people (same side of street); number of dominant building colours(both sides of street); number of buildings (both sides of street); presence of outdoor dining (same side of street); number of accent colors (both sides of street); number of pieces of public art (both sides of street) (Ewing & Handy, 2009: 81).

5.2 Methods of assessing visual complexity based on information units

5.2.1 Methods Based on Image Statistical Features

A group of studies uses statistical image processing methods to assess urban visual complexity. Common examples of statistical features related to complexity include local contrast statistics, spatial frequency, Pyramid of Histograms of Orientation Gradients (PHOG), Fourier slope measurements, and fractal dimension analysis.

(a) Local Contrast Statistics and Spatial Frequency: Cavalcante et al (2014) propose a method for assessing perceived complexity in street views based on local contrast statistics and spatial frequency. This method uses statistics to highlight structural or morphological patterns in street views related to complexity perception. The results showed a high correlation with objective rankings, indicating the method's accuracy in measuring environmental visual complexity (Cavalcante et al., 2014: 1).

In this research process, participants first categorized street views into three groups (simple, ordinary, and complex) based on their perception and ranked the images within each group by increasing complexity. Thus, a street's ranking position (or group division) is a random variable. The probability distribution of this variable is calculated by counting how often the image was placed by participants in each rank position. This probability distribution is illustrated in following formula (Cavalcante et al., 2014: 2). For each street scene, the mean "r" of its rank position probability distribution is calculated using the standard definition of the mean:

$$r = \sum_{i=1}^{76} [i \cdot p_i] = \sum_{i=1}^{76} \left[i \cdot \frac{v_i}{40} \right]$$

Finally, street views are ranked based on their mean "r". The groups are also included in the ranking (Cavalcante et al., 2014: 3). In image analysis, the RGB image is first converted to black and white, and the standard deviation of the pixel intensity in the grayscale image is calculated. A Kurtosis or K map is used for segmenting the local spatial frequency in the landscape.

(b) Histogram of Oriented Gradients (HOG): Complexity based on the histogram of oriented gradients (HOG) is defined as the mean magnitude of changes in luminance or color in an image. The higher this metric, the more objectively complex the image is (Van Geert & Wagemans, 2018: 4).

(c) Fourier Slope: Represents the strength of low spatial frequencies (coarse details) relative to high spatial frequencies (fine details) in an image. A slope value of -2 indicates that the image has fractal-like and scale-invariant properties, meaning the relative strength of low and high spatial frequencies remains constant when zooming in or out of the image. Images with a lower slope (higher than -2 values) have more prominent high spatial frequencies, while images with a steeper slope (lower than -2 values) emphasize low spatial frequencies (Van Geert & Wagemans, 2018: 5).

(d) Fractal Dimension: In natural phenomena, patterns often repeat across various scales, a concept known as fractal geometry. The fractal dimension measures how self-similar an image is, indicating the similarity between the overall image and its components. Fractals show consistent structures or patterns upon magnification (Van Geert & Wagemans, 2018: 5). Research shows that patterns with mid-range fractal dimensions are preferred and perceived as more natural (Asa et al., 2010: 115). Fractal characteristics can also be found in artificial elements, such as urban structures (Boeing, 2018: 10). Fractal dimension serves as an indicator of landscape complexity and remains consistent across scales (Asa et al., 2010: 115). It can also be applied to the analysis of urban structures and land use. Measurement methods include the Hausdorff and box-counting dimensions. Fractals, such as the Eiffel Tower, combine scaling and visual complexity (Boeing, 2018: 10), making fractal dimension a useful tool for assessing complexity regardless of scale. One method for generating fractal patterns and calculating fractal dimension in the design process is the use of Voronoi diagrams (Marzi, 2017: 9).

5.2.2. Image compression-based methods

Since the latter half of the 20th century, a theoretical framework for visual data has evolved, including Visual Complexity Theory, Algorithmic Information Theory (AIT), and Kolmogorov Complexity Theory (Donderi, 2006: 84). AIT combines information theory and computational theory, defining algorithmic complexity as the length of the shortest algorithm for a given binary string (Marin & Leder, 2013: 3). This concept is applied in data compression, where the compression algorithm generates a compressed file that, when decoded, reconstructs the original bit string (Donderi, 2006: 86). According to Solomonoff's (1986) invariance principle, the length of the code representing the probability (or complexity) of a symbolic string remains constant, correlating with subjective visual complexity (Donderi, 2006: 86). Image compression techniques such as GIF, JPEG, ZIP, PNG, and TIFF are used to measure image complexity (Van Geert & Wagemans, 2018: 6).

5.2.3 Edge detection-based methods

In addition to data compression methods, edge detection algorithms are reliable for assessing overall visual complexity (Marin & Leder, 2013: 4). These algorithms detect changes in intensity at image edges, with more edges correlating to higher perceived complexity (Marin & Leder, 2013: 4). Other measures of shape complexity include the number of edges, total edge length (Dramstad et al., 2001), and edge density (Asa et al., 2010: 115). Techniques for edge detection and image compression show high correlation with subjective visual complexity and can predict perceptual complexity.

5.2.4 Isovist methods

Isovist (Benedikt, 1979) refers to a convex hull of visible points from a specific location. The shape and size of an Isovist can vary with position (Platosh, 2017: 30). Benedikt proposed using variance and skewedness of the radials as compactness/complexity indexes as indicators of Isovist compactness/complexity, with circularity serving as a relative measure, considering a disk as the most compact form (Kwon, 2007: 60).

Statistical concepts such as Eigenvalues, first-order sequential dependencies, spatial autocorrelation, and Shannon entropy (1948) are used to explain Isovist predictability (or complexity) and elongation (Kwon, 2007: 60). Seto's study used Isovist to measure visual permeability as a factor affecting complexity, with higher visual permeability exposing more variables to the observer (Seto, 2008: 31). While useful for examining urban configuration complexity, this method may not fully address the visual complexity of detailed architectural forms.

5.2.5. Visual Diversity indicators

A variety of indicators in landscape architecture are employed to describe different aspects of richness and diversity concerning landscape features and perceptual values. The simplest indicators measure the number of landscape elements and/or the diversity of land cover types. More advanced indices combine several classes and ratios to produce a single value representing the diversity or uniformity of a landscape. These include various evenness and dominance indicators, as well as different diversity indicators (Asa et al., 2010: 114). While these indices allow for the description of the number and range of landscape elements, they provide limited information about spatial arrangement (Asa et al., 2010: 114). The spatial organization of landscape patterns is an important component for describing perceived complexity, as it mediates the role of richness and diversity in complexity. Particularly regarding the perception of coherence in a landscape, it is crucial for indicators to provide information about both the arrangement of units and their repetition (patterns) in the landscape (Asa et al., 2010: 114). Therefore, despite their effectiveness in measuring and ranking visual complexity, these indices are not suited for analyzing the spatial arrangement of elements.

5.2.6. Clumpiness indicators

Indicators used to measure landscape "Clumpiness" include the Aggregation Index (AI) (He et al., 2002), the Interspersion and Juxtaposition Index (IJI) (Lausch & Herzog, 2002), and the Contagion Index (de la Fuente de Val et al., 2006). The Contagion Index (CI) was first proposed by O'Neill et al. (1988) and later refined[1]. Dramstad et al. (2001) introduced the H index as an alternative, which inversely describes spatial heterogeneity in a landscape. The H index measures the tendency of landscape elements to differ from one another and has been shown to have a strong correlation with landscape preference (Asa et al., 2010: 115). The use of spatial autocorrelation, suggested by Pearson (2002) and Turner et al. (1991), for describing Spatial Heterogeneity is less explored. Spatial autocorrelation measures spatial dependence in data by describing similarity as a function of distance, such as how similar objects are when they are close to each other. Thus, spatial autocorrelation can serve as a starting point for analyzing coherence in a landscape by describing the degree of repetition (Asa et al., 2010: 115).

5.2.7. Utilization of shannon information theory

In the development of the concept of synergy, Haken (1983) proposed a mathematical formalism in various forms, one of which is termed the Synergetic Computer. This approach describes complex systems as a Neural Network. Using Haken's Synergetic Computer theory, Haken and Portugali (1996) developed a model known as SIRN. This theory employs Shannon Information Theory to examine perceptual complexity during movement. Shannon and Weaver (1949) introduced the concept of information as a pure quantitative measure, devoid of meaning. Shannon Information (SHI) deals with the capacity of informational channels, which refers to the amount of information originating from a specific information source and reaching a designated destination (Portugali & Haken, 2018: 148). In this system, the information source is the entity that transmits the information. The common metric for Shannon information is the Information Bit, which defines information based on entropy as follows:

$$i = -K\Sigma p \ln p$$

where K is a constant related to log2. This definition allows for the calculation of the entropy (information) i of any signal using known p, which is the relative frequency (or probability) of symbol distribution, distinguished by the index K (Portugali & Haken, 2018: 149). Since the introduction of Shannon's information theory, it has formed the basis for discussions about information across various fields. One early application in the realm of cognition was in Gestalt theory, where Attneave (1959) demonstrated that "a good Gestalt is a form with a high degree of internal redundancy[2]," implying that different geometric shapes convey varying amounts of information that can be quantified using SHI bits. Inspired by Attneave's work, Portugali and Haken (2003) showed that the same principle applies to cities; that is, different urban elements and their configurations provide varying amounts of information, which can be quantified using Shannon's theory bits (Portugali & Haken, 2018: 149). As emphasized by Shannon and commonly accepted in information theory studies, Shannon information disregards the meaning of the message. According to Brillouin's interpretation, "information is devoid of meaning." However, Portugali and Haken's study found that in their case study of "cityscape," the meaning of information is "transformed" into Shannon's mathematical definition of information (Portugali & Haken, 2018: 149), and it can be used as a method to quantify visual information derived from urban form.

[1] - The formula for calculating the contagion index (CI) is as follows:

$$CI = 1 + \left[\left(\sum_{i=1}^{n} \sum_{j=1}^{n} P_{i,j} \right) \ln(p_{i,j}) \right] / 2\ln(n),$$

where "n" is the number of species in the landscape, "pi,j" is the total number of times species "I" is adjacent to species "j", divided by the total number of times species "I" is adjacent to all other species, including itself. The CI (Contagion Index) ranges from 0 to 1, with 0 indicating the lowest level of contagion.

[2] -**Redundancy in Engineering** refers to the inclusion of similar subsystems arranged in parallel within a system to ensure the overall functionality of the system under emergency or fault conditions. The term "system" in this context can refer to either a physical entity or an operational system. For instance, **path redundancy** in communication systems is defined as an additional path between two points in the network graph, which serves as a backup route.

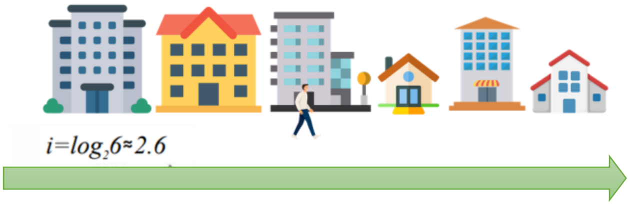

Fig. 8. Top: Walking down a street where all the buildings are identical; Bottom: Walking down a street where each building is distinct (Portugali & Haken, 2018: 155).

6. Typology of Visual Complexity Measures

The evaluation indicators of visual complexity in the urban environment vary based on the assessment method, whether they are applied to urban components and elements, or whether they assess environmental elements as information-bearing messages. These indicators differ in their evaluation scale and the components they cover, leading to diverse applications in both academic studies and practical urban design. The visual complexity indicators in the urban environment are presented in a table. 3 according to these four criteria:

Table 3
visual complexity measures

Reference	Evaluation scale	Elements/characteristics to be evaluated	Indicator	Evaluation method
Krampen,1979: 245	Level 2	Subjective measurements: semantic differential scales of complexity, three objective measurements: 1-Type/token ratio. The visual elements: (Sky, roof, wall, balcony, decoration, display window, door, or advertising)	Type/token ratio	Urban Landscape Elements as Messages
Elsheshtawy ,1997	Level1 to level 4	Overall massing, secondary volumes, openings, texture(s), width, and height. Complexity: sum of the number of types of each element in the assembly.	-	
Stamps,1998b	Level1 to level 4	The number of vertices, Symmetry, Variation in the lengths of line segments, and Variation in angle sizes. The number of rotations in the overall form outline.	-	
Stamps ,2000	Level4 to level 6	Surface complexity, silhouette complexity, facade articulation	Psychology and the Aesthetics of the Built Environment	
Portella, 2016	Level4 to level 6	Facade silhouette, Facade details, and/or Facade articulation, Visual character, Colour variation, Symbolic meanings (six variables of the built environment that can carry meanings: building configuration, spatial configuration, materials, nature of illumination, colour, and non-visual environment such as sounds and the tactile and olfactory qualities of surfaces and textures.)	Complexity Method	
Ewing, R. & Clemente, O. ,2005	Level 1	Number of buildings , primary building colors, accent colors, Presence of outdoor dining, Number of pieces of public art, Number of pedestrians	Measuring Urban Design Qualities: An Illustrated Field Manual,2005 (Quality of complexity)	
Heath et al, 2000	Level 1	Calculating the complexity of silhouette for symmetrical buildings (Css) Css = (number of straight segments and number of ornamental projections) x (number of curved or sloping segments). Calculating the complexity of silhouette for asymmetrical buildings (CSA) Csa = (Calculated ComSA + number of straight segments + number of ornamental projections + 2(number of curved or sloping segments).	Estimating complexity of the tall buildings seen at a distance	

Van Geert & Wagemans,2018	Level 1 to Level 6	Image processing by computer: The mean magnitude of changes in luminance or color in an image. The higher the value of this measure, the more objectively complex the image is.	Pyramid of Histograms of Orientation Gradients (PHOG)		
Cavalcante et al, 2014	Level 1 to Level 6	Image processing by computer: RMS (root-mean-square) contrast RMS (root mean square) contrast is defined as the standard deviation of pixel intensities, commonly applied for non-periodic targets (noise, textures and images.	local contrast		
Cavalcante et al, 2014	Level 1 to Level 6	Image processing by computer After local contrast calculation, the kurtosis map K is used to segment the local spatial frequency in the scene. The computation starts by firstly log-transforming luminance values in each neighborhood, i.e., This non-linear transformation reduces large differences between luminance intensities in different parts of the image.	Spatial frequency	Statistical features of the image	
Redies, Brachmann, & Hayn-Leichsenring, 2015 Redies et al., 2014 Van Geert & Wagemans,2018:5	Level 1 to Level 6	In images with a shallower slope (values higher than -2), high spatial frequencies are more prominent than in image with a slope of -2. In images with a steeper slope (values lower than -2), low spatial frequencies are more important.	Fourier slope		Information as Messages
Asa et al,2010:115; Boeing,2018:10	Level 1 to Level 6	Hausdorff dimension	Fractal Dimention		
Shen, 2002: 419	Level 1 to Level 6	Box-counting dimension			
Donderi,2006a:84	Level 1 to Level 6	Image scanning on a computer and storage in various formats (including Bitmap, GIF, JPEG, ZIP, PNG, and TIFF) serves as a symbol string.	Bitmap ،GIF ، JPEG، zip، PNG	Image compression techniques	
Forsythe et al. ,2008, 2011; Gartus & Leder ,2017; Marin & Leder ,2013.	Level 1 to Level 6	Image processing by computer A contour-based and a global measure of shape.	Perimeter Detection		
(Baessler & Klotz, 2006)	Level 1 to Level 6	Image processing by computer The ratio of the total length of edges in a network or image.	Edge Density (ED)	Edge detection algorithms: Detection of changes in intensity at an image's edges	
Forsythe et al. (2008, 2011); Gartus & Leder (2017); Marin & Leder (2013)	Level 1 to Level 6	Uses Canny-algorithm (developed by John F. Canny in 1986) to detect weak edges appearing in combination with strong edges in grayscale images.	Canny edge detection		
Dramstad et al. (2001)	Level 1 to Level 6	Calculated based on the number and size of patches in images.	Total edge length		
Benedikt,1979 Kown, 2007:60	Level 1	Eigenvalues, First-order sequential dependencies, Spatial Autocorrelation and Shannon's (1948) entropy in information theory.	Predictability (Complexity) Elongation	Isovist	

Seto,2008:31	Level 1	Factor influencing the complexity (with the assumption that the higher the visual penetration, the more variables are exposed to the observer)	visual penetration	
Asa et al,2010:114	Level 1 to Level 6	By describing the abundance or rarity of a species, it becomes possible to characterize the number and range of landscape elements; however, limited information is provided regarding their spatial arrangement.	Evenness indicators	Diversity indicators
Asa et al,2010:114 Hunziker & Kienast, 1999; Lausch & Herzog, 2002	Level 1 to Level 6	The abundance of a species relative to other environmental elements, in terms of size, population, and other factors, indicates a low level of environmental diversity..	Dominance indicators	
Asa et al,2010:114 Dramstad et al., 2001; Hunsaker et al., 1994	Level 1 to Level 6	The Shannon index is the most commonly used method for quantitatively assessing species diversity and is calculated using the following equation: $H = -\sum_{i=1}^{S} p_i \ln(p_i)$	Shannon Diversity Index (SDI) and Shannon Evenness Index (SEI)	
He et al., 2002 Asa et al, 2010;115	Level 1 to Level 6	Measures the extent to which similar patches are clustered together in a landscape. It is calculated using an adjacency matrix that considers the number of like adjacencies (joins) between pixels of a specific patch type.	Aggregation Index (AI)	Clumpiness indicators
Lausch & Herzog, 2002	Level 1 to Level 6	Measures the degree of intermixing or adjacency of various patch types.	Interspersion and Juxtaposition Index (IJI)	
de la Fuente de Val et al., 2006	Level 1 to Level 6	Assesses how contiguous or dispersed various patch types are within a given area.	Contagion Index (CI)	
Dramstad et al. 2001	Level 1 to Level 6	Describes the inverse of clumpiness, spatial heterogeneity, in the landscape. The H-index measures the tendency for adjacent landscape patches to be different from one another.	H-index	
(Cliff & Ord, 1973) Pearson, 2002 Turner et al,1991	Level 1 to Level 6	Spatial autocorrelation measurements explores the spatial dependency in the data through describing similarity as a function of distance, for example, how similar are objects located close to each other.	Spatial Autocorrelation	
Portugali & Haken, 2018	Level 1 to Level 6	Using Synergetics – Haken's theory of complex, self-organizing systems(1983) – Synergetic inter-representation networks (SIRN) model was extracted. This theory employs Shannon's information theory to examine perceptual complexity during movement.	Synergetic Inter-representation Networks (SIRN)	Information Theory
Krampen,1979: 245	Level 2	Three objective measurements: 2-Entropy of the façade/ 3-Entropy based on the transitions between each cell in the grid.	Entropy	

Given the multiplicity and diversity of visual complexity metrics, recent approaches have sought to integrate various indicators through computational methods. Computer-based and AI-driven innovations have significantly advanced the prediction and analysis of visual complexity perception. Various computational tools, such as ImageJ, offer sophisticated analytical methods, including edge detection, fractal dimension calculation, and Shannon entropy measurement, to assess visual complexity (Marzi et al., 2024, p. 62). Additionally, datasets like SAVOIAS provide a structured resource for evaluating visual complexity across diverse image categories, employing crowdsourced pairwise comparison techniques to generate absolute complexity scores (Saraee, Jalal, & Betke, 2018). The introduction of Multi-Scale Structural Complexity (MSSC) further refines this analysis by considering hierarchical dissimilarities across different scales, ensuring a more intuitive and consistent correlation with subjective complexity judgments (Kravchenko et al., 2024). Moreover, machine learning methodologies enhance visual complexity assessment through feature selection and outlier analysis, optimizing predictive accuracy. For instance, Feature Selection Multiple Kernel Learning has demonstrated a strong correlation (0.71) with human perceptions of complexity, signifying its efficacy in bridging computational analysis with human aesthetic evaluations (Fernandez-Lozano et al., 2019). These technological advancements contribute to a deeper understanding of visual complexity, facilitating applications in cognitive psychology, computer vision, and urban design.

7. Discussion

Despite the significant functional and emotional effects of visual complexity on the human mind and the long history of studies on optimal complexity across various fields, there remains considerable disagreement regarding the methods for defining and measuring visual complexity. This gap in the research is especially noticeable in studies involving real-world data and urban environments. Most research in this area has focused on abstract and highly simplified data from laboratory settings, particularly in relation to the aesthetic value of complexity from an emotional perspective. This lack of consensus can be attributed to the inherent difficulty in defining complexity, especially objective visual complexity in three-dimensional space, and measuring perceived complexity influenced by it. As a result, there is minimal agreement on how to define, measure, and assess the functional effects of complexity. The present study aims to contribute to the understanding and integration of perceptual visual complexity in urban environments by offering a comprehensive review of relevant indicators. These indicators for assessing visual complexity can also be applied to real-world settings, potentially reducing the fragmentation in existing studies.

Given the nature of both objective and subjective visual complexity indicators, as discussed earlier, and the strengths and weaknesses of each—particularly the exclusion of familiarity with the environment, the influence of other senses on visual complexity perception in urban settings, and the lack of scale-specific analysis by objective indicators, as well as the influence of personal traits and semantic factors on subjective complexity perception- this study proposes a balanced approach that combines both types of indicators. This approach acknowledges the multidimensional nature of complexity, using a wide range of objective measures alongside subjective categorization (Marin & Leder, 2013: 1). This combined approach is expected to yield more accurate results in studies.It is also important to note that most of the mentioned indicators have been tested in laboratory environments with abstract data. For their application in urban contexts, it is essential to first carefully assess their validity.

Studying the visual complexity of urban forms imposes specific methodological requirements on research, and failure to anticipate these requirements can affect the generalizability of study results. Research should primarily focus on visual perception, although the influence of other senses should not be overlooked. Movement plays a crucial role in the perception of visual complexity, and given the goal of this study—to analyze visual complexity from the perspective of pedestrians—this factor must be carefully considered in practical assessments. A potential solution for future research is the application of Virtual Reality Modeling (VRM) (Shakibamanesh, 2014, p. 130). The use of semi-experiments within virtual environments allows for the control and manipulation of various variables, including non-visual components of complexity, thereby facilitating the simulation of real-world factors.

The scale of visual complexity studies in urban areas is highly influential and must be clearly defined and consistent across studies. Additionally, the importance of the semantic dimension in environmental perception must be taken into account. Familiarity with the environment should also be controlled as a key variable in empirical studies.

history of research on the principle of balance between order and complexity—often referred to as "unity in variety" as a fundamental aesthetic principle, there remains a notable gap in empirical studies that directly investigate this balance (Post et al., 2016). Like complexity, order has been conceptualized in various ways within the existing literature. However, systematic research on order seems to be less prevalent compared to complexity. Additionally, while the distinction between objective and subjective order is logical, it is not commonly used in the literature. Objective order refers to the physical structure and organization inherent in a specific stimulus (e.g., symmetry, repetition, alignment), which differs from subjective order, involving individuals' perception of the arrangement of the stimulus (Van Geert & Wagemans, 2018: 13). Understanding the interplay between order and complexity, as well as the types and nature of ordering in the urban built environment, is essential for achieving a proper understanding of optimal complexity in urban environments.

8.Conclusion

This has underscored the complexities of defining and measuring visual complexity in urban environments, emphasizing the necessity of a multidimensional approach that integrates both objective and subjective indicators. The proposed typology of visual complexity measures provides a structured framework that accommodates different scales and perspectives, enhancing the applicability of complexity assessment in urban studies. The findings highlight the critical role of movement, familiarity, and semantic factors in shaping visual complexity perception, suggesting that future studies should incorporate Virtual Reality Modeling (VRM) to simulate real-world experiences effectively. Furthermore, the interplay between order and complexity remains a crucial but underexplored area that requires further empirical investigation. By bridging the gap between computational models and human perception, this research contributes to a more comprehensive understanding of urban form complexity, ultimately aiding in the development of visually stimulating yet cognitively manageable urban environments.

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