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Doctoral Dissertation

Study of Urban Park Landscape Visual Quality in China: Multidimensional Assessments of Perception, Emotion, and Stress Recovery

LIU, Chong

Supervisor Takaya Yuizono

Graduate School of Advanced Science and Technology
(Knowledge Science)

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Abstract

Urban parks play a vital role in enhancing the quality of life, particularly in rapidly urbanizing countries like China, where the rapid expansion in the quantity of urban parks has not always been accompanied by a corresponding improvement in their quality. Poorly designed parks not only fail to fulfill their intended purposes but can also result in resource wastage and dissatisfaction among users. This dissertation addresses these challenges by focusing on the Landscape Visual Quality (LVQ) of urban parks in China, providing an evidence-based framework for improving both the aesthetic and functional aspects of park design while catering to the unique needs and preferences of Chinese users.

The research is structured into three interrelated studies, each contributing to a comprehensive understanding of how LVQ impacts human perception, visual behavior, emotions, and stress recovery:

Study 1 develops a comprehensive evaluation system for assessing urban park LVQ using multidimensional visual indicators, including eye-tracking data, image segmentation, and spatial feature indicators. Through GEE logistic regression models, the study identifies key positive and negative factors influencing seven perceptual dimensions, including beauty, comfort, color, complexity, liveliness, greenness, and safety. Integrating these multidimensional visual indicators, a generalized estimating equations (GEE) logistic regression model demonstrated superior performance over existing traditional models focusing only on spatial features, facilitating more accurate evaluations of LVQ perception. Moreover, herb plants (eye-tracking indicator), water ratio (image segmentation indicator), and number of materials (spatial feature indicator) were the most positive factors affecting human perception. Isolated planting style positively impacted the perception of greenness, and sky ratio negatively correlated with beauty perception. Additionally, openness levels of 20–80% enhanced beauty perception, while openness above 80% decreased liveliness but improved safety perceptions. Shrub species diversity positively correlated with perceptions of greenness and complexity, whereas single and dense shrub arrangements diminish perceptions of greenness and liveliness. Overall, this study provides valuable insights for urban planning at the design stage to enhance decision-making and visual quality of urban parks, thereby contributing to the establishment of more sustainable urban development strategies.

Study 2 focused on the emotional dimension of LVQ. This study quantifies how seven landscape elements influence emotional responses and visual behavior. Herb plants most effectively promote both psychological and physiological emotional responses, making them the most emotionally beneficial natural element. Shrubs and artificial objects are associated with negative emotional responses, requiring careful proportion and spatial arrangement. Flowering trees simultaneously decrease pulse rate and increase skin conductance, indicating a compound emotional state of calmness and alertness. To support emotional restoration, designated restorative zones should minimize artificial elements and incorporate water features and herb plants. By bridging perception and emotion, this study provides practical recommendations for urban park design to foster positive emotional experiences.

Study 3 examines the potential effects of urban park landscapes on children's emotional and stress recovery, contributing child-focused perspectives to the LVQ framework. The findings suggest that LVQ may be associated with landscape element proportions and spatial openness. For children, while greenery remains important, spatial openness seems to play a more prominent role in shaping children's emotional responses. Landscape features may impact children's emotions, particularly calmness, happiness, and disgust, suggesting that thoughtful spatial arrangements and visual balance could contribute to child-friendly landscape design.

This research synthesizes findings from the perceptual, emotional, and stress recovery dimensions of LVQ to develop a comprehensive set of optimization guidelines for urban park design. These guidelines integrate evidence-based recommendations across multiple dimensions, offering a practical framework for balancing aesthetic, emotional, and functional objectives in park planning. By aligning user-centered insights with multidimensional evaluation methods, this dissertation provides urban planners and landscape designers with actionable tools to create inclusive, visually engaging, and emotionally supportive urban parks. This contribution not only advances the understanding of LVQ but also supports the broader goal of sustainable urban development, addressing the well-being priorities of diverse user groups, including children, in rapidly urbanizing regions like China.

Keywords: Urban park, Virtual reality, Eye-tracking, Human perception, Emotion responses, Physiological signal.

Acknowledgment

As I stand at the threshold of completing this doctoral journey, I find myself reflecting on the myriad of experiences, challenges, and triumphs that have shaped this work. This dissertation is not just a product of my efforts, but a culmination of the support, inspiration, and guidance of many remarkable individuals.

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As I close this chapter of my life, I am reminded of the words of Rainer Maria Rilke: "The only journey is the one within." This dissertation represents not just an academic accomplishment, but a journey of the soul—a journey that has been deeply enriched by the presence and support of all those who have walked alongside me. For this, I am eternally grateful.

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Chapter 1

Introduction

1.1 Research background

Urban green spaces, especially urban parks, are essential components of urban ecosystems and play a crucial role in promoting human health and well-being [1]. Against the backdrop of rapid urbanization, these green spaces not only provide necessary contact with nature for urban residents but also help mitigate urban heat island effects [2], improve air quality, and reduce noise pollution levels [3]. Numerous studies have shown that regular contact with urban green spaces can alleviate psychological stress [4], reduce anxiety [5] and depression symptoms [6], promote physical health [7], and increase social interactions [8], thereby enhancing the quality of life and social welfare. However, the rapid expansion of urban parks in China has not been accompanied by corresponding improvements in quality. Poorly designed urban parks not only fail to achieve their intended effects but can also lead to resource wastage and social issues. For instance, research indicates that excessive enclosure in parks may reduce people's sense of security [9], and park features can influence crime rates [10]. Moreover, disparities in the quality of urban parks across different regions exacerbate social inequality, posing challenges to achieving public health equity [11,12]. Therefore, assessing the visual quality of urban parks at the early stages of urban planning is particularly important [11].

Although landscape visual quality (LVQ) has attracted increasing scholarly attention, several key challenges persist in current research. Firstly, LVQ research remains limited in rapidly urbanizing regions such as Asia, despite the alterations in urban green space planning and use patterns driven by accelerated development [13]. Existing studies have largely focused on Western contexts, with limited attention to how different urban development patterns and cultural values may shape park use and perception [**?**, 14–17]. Secondly, traditional LVQ evaluation methods—such as the scenic beauty estimation method [18], analytic hierarchy process [19], and semantic differential technique [20]—rely on subjective interpretation and specialized terminology, often leading to inconsistency and measurement bias [21]. Moreover, the inherent complexity of human visual perception makes it difficult to accurately capture images, thereby limiting the precision of LVQ assessments [22]. Building robust classification models based on assessment results to better understand and categorize human perceptions of landscapes remains a key challenge. Therefore, improvement of existing assessment methods and development of strategies to convert the assessment results into actionable insights are necessary to ensure that urban park designs meet the expectations and needs of future urban residents.

In addition to visual perception, emotional experience constitutes a critical dimension in evaluating the LVQ of urban parks. The compact city approach and densification have reduced green space quality and increased the risk of low-quality green spaces, thereby undermining urban livability [23]. The decline in environmental experience not only affects ecological balance but may contribute to increased psychological stress among urban residents and weaken their emotional regulation capacity [24]. A growing body of research has recognized the therapeutic potential of well-designed urban parks, highlighting their ability to enhance emotional well-being [25, 26]. To better understand how environmental features influence emotional states, scholars have employed various assessment methods, including self-report surveys, physiological signal monitoring, and facial expression analysis [27–29]. Despite advancements in emotion measurement, research on emotional responses in urban parks continues to rely on indirect data acquisition methods. Visual information plays a crucial role in variations in landscape perception [30]. However, standardized frameworks and quantitative methods linking visual behavior to emotional responses remain underdeveloped. An integrated approach combining multimodal emotion assessment and visual behavior analysis is needed to develop standardized frameworks linking park elements to emotional responses.

While most studies on LVQ focus on adult users, children—who are sensitive to environmental stimuli—remain an underrepresented group in current research. However, evidence suggests that children perceive landscape elements differently than adults. For instance, a photo-projective study comparing perceptions of a river environment found marked differences between children and adult residents, highlighting the need for age-specific design considerations [31]. Moreover, although nature exposure has been linked to improved emotional well-being and stress regulation in children, most research has concentrated on adults [32, 33]. Studies have demonstrated that green environments can support children's creativity, social interaction, and emotional development [34], yet urban planning often fails to prioritize their needs [35]. In addition, conventional methods for assessing children's emotional states—such as questionnaires, interviews, and parental observation—often rely on indirect inference and may not capture real-time emotional responses. Empirical studies directly measuring children's emotional responses to landscape composition remain limited.

1.1.1 Urban park landscapes

The definition of urban parks varies across different academic disciplines due to their broad scholarly backgrounds, leading to diverse perspectives on what constitutes a park. Additionally, the dynamic evolution of parks complicates the establishment of a universally accepted definition. Historical perspectives have contributed to the richness of the concept, but a consensus remains elusive. Historically, the notion of urban parks has evolved from mere recreational spaces to complex entities that embody the interplay of nature and urban culture. In the 1920s, J.C. Loudon advocated for parks as a means to enhance the rational attributes of society's lower strata [36]. Later, in 1938, Holger Blom, a Swedish landscape architect, described parks as "a re-creation of nature on the foundation of existing natural conditions, combined with cultural elements" [37]. M. Laurie, reflecting on the 19th century, viewed urban parks as a natural retreat within industrial cities, suggesting their role as green lungs amidst urban sprawl [38]. In China, the conceptualization of parks began with Mr. Chen Zhi in 1928, who is considered a pioneer of Chinese landscape architecture. He categorized parks under 'Community Landscape', a sub-discipline of Landscape Architecture, emphasizing their educational, health, and safety functions [39]. By 2003, scholars like Meng Gang and Li Lan were defining urban parks from a functional perspective, seeing them as naturalized spaces designed for recreation and various other community services [40]. This functional perspective was formalized into a national standard by the Ministry of Housing and Urban-Rural Development in 2017, which described parks as publicly accessible green spaces with facilities for recreation and areas serving ecological and aesthetic purposes.

Today, urban parks are recognized for their multifunctional roles, catering not only to recreation but also to community safety [9], health [12], and ecological sustainability [2, 3]. These parks are integral to urban infrastructure, serving as critical components for enhancing urban life quality through physical comfort, psychological relief, and facilitating social interactions [4,8]. The extensive benefits of interacting with nature, documented in numerous studies, highlight the crucial role of urban parks in mitigating urban heat island effects, purifying the air, and providing a respite from the bustling city life [2, 3]. As urban areas continue to evolve, the design and functionality of parks remain pivotal in shaping healthier and more sustainable urban environments.

1.1.2 Landscape visual quality

Visual perception plays a decisive role in how individuals evaluate the landscape visual quality (LVQ) of urban parks, with studies indicating that visual information accounts for 76% of urban park satisfaction [30, 41]. LVQ is defined as the interaction between landscape attributes and human perception, shaping how individuals experience and assess urban environments [42]. A deeper understanding of visual perception can inform strategies to enhance park design and optimize user experiences [43]. Urban parks consist of diverse landscape elements that integrate both aesthetic and functional properties, and their evaluation, based on perceptual and qualitative judgments, serves as a critical foundation for urban planning and design decisions.

Despite growing recognition of the role of urban landscapes in mental health promotion, research on the specific mechanisms through which green spaces influence psychological well-being remains limited [44]. This knowledge gap has led to oversimplified planning approaches, where urban green spaces are often evaluated solely based on size and coverage, without fully considering their actual usability and engagement potential. As a result, some urban parks become underutilized "green seen but not frequented" spaces, failing to provide the intended psychological benefits or a sense of safety for visitors [45]. This highlights the need for more evidence-based design strategies that consider both visual and experiential qualities of urban parks. The COVID-19 pandemic further underscored the importance of well-designed and accessible urban landscapes, bringing environmental justice and spatial accessibility to the forefront of urban planning [46]. The increased reliance on public green spaces during lockdowns highlighted existing inequalities in park distribution, accessibility, and quality, challenging conventional urban planning paradigms [47]. These circumstances stress the urgency of rethinking urban green space design, ensuring that parks are not only visually appealing but also psychologically restorative and equitably accessible. Therefore, urban planners and researchers must adopt a more comprehensive approach to landscape evaluation, integrating visual, perceptual, and emotional dimensions to enhance the effectiveness of urban green spaces in promoting public well-being.

1.1.3 User perception and landscape visual quality

As urban populations grow, urban designers often prioritize the physical layout of spaces while overlooking their psychological and emotional impact. This oversight has led to the creation of visually appealing but emotionally disconnected environments that fail to foster engagement or enhance users' well-being [48]. For instance, public dissatisfaction with Tadao Ando's concrete café in Manchester's Piccadilly Gardens (2016) and design issues with London's South Bank public spaces in the late 20th century highlight how urban landscapes that neglect users' psychological and functional needs can lead to costly redesigns and resource wastage. To create effective urban spaces, designers must move beyond aesthetic considerations and focus on how landscapes facilitate emotional recovery and visual interaction. This requires an evidence-based approach, where user data informs design decisions, recognizing that humans are active agents in shaping their built environment. Increasingly, landscape perception is studied through physiological, psychological, and sensory dimensions [49, 50]. In the assessment of scenographic spaces, the physical environment does not merely serve as a backdrop but actively shapes emotional and perceptual experiences. Contemporary urban design increasingly integrates digital technologies and human-centric methodologies to capture user feedback and optimize spatial planning. By leveraging advanced data collection techniques, designers can analyze emotional responses, visual experiences, and spatial interactions with greater accuracy (Figure 1.1). Such an approach ensures that urban spaces fulfill their intended functions, enhancing usability, user satisfaction, and the LVQ of urban environments.

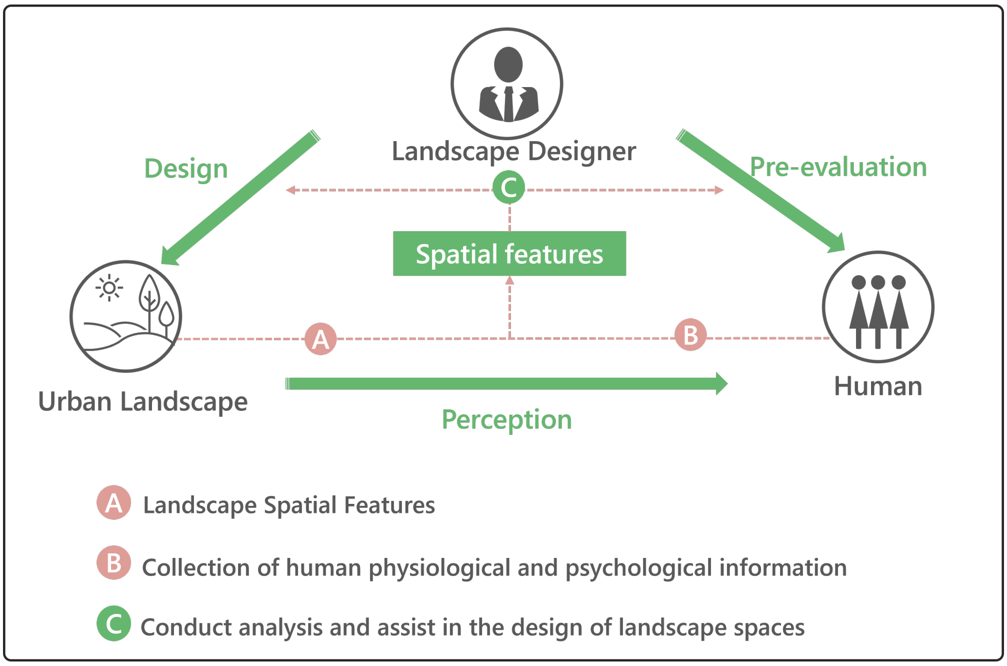

Figure 1.1: Landscape design workflow

1.1.4 Interdisciplinary interactions in landscape design

With the increasing emphasis on human-centered urban design, there is a growing need to understand how users perceive and interact with landscape spaces. Traditional evaluation methods rely on questionnaires and expert assessments, which are often subjective and lack real-time behavioral data. Recent advancements in computer science, VR, and physiological sensing technologies have provided new tools for quantifying user perception and optimizing landscape design. These interdisciplinary innovations allow researchers to create immersive, data-driven environments where users' visual attention, cognitive responses, and physiological states can be accurately measured [51]. Figure 1.2 presents a conceptual model for capturing human spatial perception data across multiple dimensions in VR. Within visual

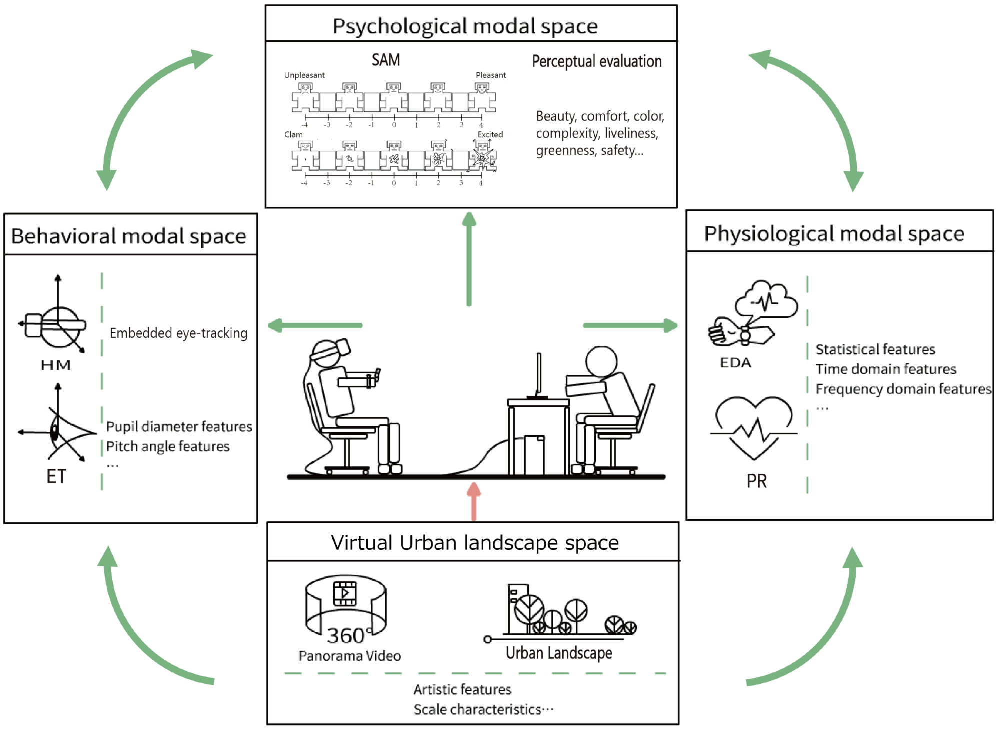

Figure 1.2: A conceptual model of human multidimensional perceptual feedback

perception analysis, eye-tracking technology provides real-time data on users' gaze behavior and fixation points, offering insights into visual preferences and attention distribution in urban spaces. By integrating eye-tracking with physiological sensing, it is possible to examine how different landscape elements influence users' emotional and cognitive states, providing empirical evidence for landscape design optimization [52]. In physiological response measurement, advanced biometric sensors capture synchronous data on heart rate, electrocardiography, electrodermal activity, respiration, and body temperature. These physiological indicators, when combined with eye tracking, provide a deeper understanding of users' emotional arousal and stress levels in response to different urban landscape settings [53, 54]. This study leverages eye-tracking and multidimensional physiological data to assess users' cognitive and emotional responses in urban landscapes. By integrating VR-based simulations, researchers can evaluate how spatial configurations affect perceived comfort, engagement, and well-being. The ability to analyze real-time user interactions in a controlled, immersive environment allows designers to fine-tune spatial arrangements before actual construction. This approach represents a shift towards evidence-based, data-driven design, bridging the gap between human perception research and practical urban landscape planning. Ultimately, these advancements provide a foundation for creating urban environments that are both functional and emotionally engaging, optimizing the dynamic interaction between people and their surroundings.

1.2 Research objectives

This dissertation aims to develop an integrative framework for assessing the LVQ of urban parks by combining quantitative landscape indicators with perceptual, emotional, and stress recovery dimensions. Through the integration of eye-tracking data, spatial features, image segmentation, physiological signals, and child-specific assessments, the research seeks to generate actionable insights for optimizing urban park design. The ultimate goal is to promote well-being, inclusivity, and sustainability in the context of Chinese urban development.

- **Sub-objective 1: To evaluate LVQ using multidimensional visual indicators.** The first study focuses on adult users and examines how spatial features, visual attention patterns, and semantic segmentation collectively influence perceived landscape quality. By constructing a quantitative evaluation model that identifies positive and negative spatial attributes, this study provides a foundation for improving the visual and experiential quality of urban parks.
- **Sub-objective 2: To explore the emotional dimension of LVQ.** The second study explores how landscape elements—such as herb plants, water landscapes, and artificial objects—influence emotional responses and visual behavior. By linking eye-tracking data with physiological signals and self-reported emotions, the study aims to clarify how visual attention mediates emotional reactions, deepening our understanding of emotionally supportive park environments.
- **Sub-objective 3: To examine the emotional and stress recovery dimensions of LVQ.** This study focuses on children, a user group often underrepresented in LVQ research. It investigates how spatial openness, greenery, and other landscape elements affect children's emotional states and stress recovery through facial emotion recognition and stress assessment. In contrast to the first two studies on adults, this research highlights the distinct perceptual and emotional needs of children, contributing to more inclusive urban park design.

Together, these three studies offer a comprehensive, user-centered approach to understanding and improving the visual, emotional, and restorative qualities of urban parks.

1.3 Research contributions

This dissertation aims to develop an integrative framework for assessing the LVQ of urban parks by combining quantitative landscape indicators with perceptual, emotional, and physiological dimensions. To achieve this, it incorporates methods such as VR-based visual exposure, eye-tracking, image segmentation, and physiological signal analysis, enabling a comprehensive and data-driven approach to LVQ assessment.

Previous studies on LVQ have often relied on subjective evaluations such as interviews, the scenic beauty estimation method, or semantic differential approaches [18, 20, 55]. These methods, while valuable, are prone to measurement errors due to their dependence on respondents' understanding of specialized terminology and lack the precision to capture complex visual experiences [21,22]. In addition, many existing studies derive visual indicators from 2D images [22, 56], which may not adequately reflect the three-dimensional and immersive nature of actual urban parks. Although recent developments in spatial metrics and computer vision techniques have enhanced indicator [57], relatively few studies have integrated these with user-centered data, such as visual attention. To address these limitations, this study introduces a VR-based assessment framework that integrates eye-tracking, image segmentation, and spatial feature indicators. Generalized estimating equation (GEE) models were constructed and validated across seven perceptual dimensions, comparing the predictive performance of models using multidimensional visual indicators against those using only spatial indicators. The results showed that the integrated models achieved moderate improvements in classification accuracy, with AUC values increasing by 1% to 7%, and lower QIC values indicating improved model fit. Among the indicators tested, herb plants (eye-tracking indicator), water ratio (image segmentation indicator), and number of materials (spatial feature indicator) were among the most consistently associated with more positive perceptual evaluations. This contribution enhances existing LVQ assessment approaches by incorporating attention-based, spatial, and semantic features into a single evaluative framework. The proposed method offers a more structured and reproducible approach to examining perceptual variation in urban parks and may support more evidence-informed strategies for improving visual quality during the design phase.

In addition to visual perception, emotional response represents a fundamental dimension of landscape experience and plays a meaningful role in shaping users' evaluations of spatial quality. Previous studies on the emotional aspects of LVQ have primarily relied on self-reported measures, such as semantic differential scales and Likert-based surveys [27, 58, 59]. While these tools offer valuable insights into participants' subjective emotional states, they are prone to individual bias and may not capture real-time or subconscious responses [28, 60]. Moreover, existing research often assesses emotional responses in isolation from visual attention processes, overlooking the mediating role of visual perception in emotional experiences [30]. To address these limitations, this study integrates electrodermal activity (EDA), pulse rate (PR), eye-tracking data, and self-assessment scales within a VR environment to explore how landscape elements—such as water landscapes, herb plants, artificial objects, and shrubs—influence both visual behavior and emotional responses. The findings reveal that herb plants most effectively promote both psychological and physiological emotional responses, making them the most emotionally beneficial natural element. Flowering trees simultaneously decrease pulse rate and increase skin conductance, indicating a compound emotional state of calmness and alertness. To support emotional restoration, designated restorative zones should minimize artificial elements and incorporate water landscapes and herb plants. By integrating multiple modalities—physiological data, self-reported emotions, and visual attention—this study contributes to a more nuanced understanding of the emotional dimension of LVQ. The findings may inform future landscape design by identifying elements that support more emotionally engaging and visually comfortable urban park environments, and they contribute to advancing LVQ research beyond traditional perception-based evaluation methods.

Although the emotional and restorative benefits of green spaces for adults have been extensively studied [32, 33], children—who are particularly sensitive to environmental stimuli—remain an underrepresented population in LVQ research. Existing studies often rely on indirect methods, such as interviews or parental observation [35], and few have directly measured children's real-time emotional responses to landscape compositions. Moreover, evidence shows that children perceive landscape elements differently than adults [31], and that environmental features can significantly influence their emotional development and social behavior [34]. To address these gaps, this study examines how the proportion of landscape elements—such as openness, greenery, and road ratio—influence children's emotional and stress recovery. Using a mixed-method approach that combines facial emotion recognition with the State-Trait Anxiety Inventory for Children (STAI-S) and the Perceived Restorativeness Scale for Children (PRCS-C II), the study evaluates emotional outcomes more objectively and in real time. The inclusion of stress recovery as an additional dimension responds to the need for understanding not only immediate emotional reactions, but also how effectively different environments support emotional regulation after mild stress.

By intentionally introducing a low-stress task prior to exposure, the study was able to capture pre-post emotional variation and quantify restorative potential. Rather than conducting the experiment in uncontrolled outdoor environments, children observed high-resolution video representations of various urban park landscapes in a quiet indoor setting. This design helped minimize external distractions such as noise, crowd movement, and weather conditions, ensuring greater consistency in visual exposure and emotional measurement. The results suggest that spatial openness enhances calmness and happiness while reducing negative emotions, whereas certain artificial objects may induce visual discomfort or hinder stress recovery. This contribution adds a child-centered dimension to LVQ research by incorporating real-time emotional and stress recovery assessments. The findings offer preliminary insights into how landscape composition may influence children's emotional responses, potentially informing future design considerations for supportive and restorative urban park environments.

1.4 Thesis structure

This thesis explores the effects of urban park landscape elements on human LVQ, emotional responses, and stress recovery, using data collected through two distinct experiments. The methodology is structured around three studies, each addressing specific research objectives derived from these experiments (Figure 1.3).

Chapter 1: Introduction This chapter sets the stage for the dissertation by examining the role of LVQ in shaping human perception, emotions, and stress recovery within urban parks. It outlines the research gaps in existing LVQ assessments and highlights the necessity of integrating multidimensional visual, physiological, and perceptual indicators into urban park evaluation. The chapter also defines the primary research objectives, demonstrating how this dissertation contributes to the broader fields of urban planning and landscape architecture by providing evidence-based strategies for LVQ enhancement.

Chapter 2: Literature review This chapter reviews existing studies on LVQ assessment methodologies and their applications in urban park research. It examines how landscape elements influence perception, emotion, and stress recovery, providing a theoretical foundation for this dissertation.

Chapter 3: Assessment of landscape visual quality using multidimensional indicators This chapter develops a comprehensive LVQ assessment framework by incorporating eye-tracking, image segmentation, and spatial feature indicators. By integrating these multidimensional visual indicators, it enhances the accuracy of LVQ classification models and provides quantitative insights into landscape perception. The findings contribute to a more systematic evaluation of LVQ and offer practical recommendations for improving urban park design.

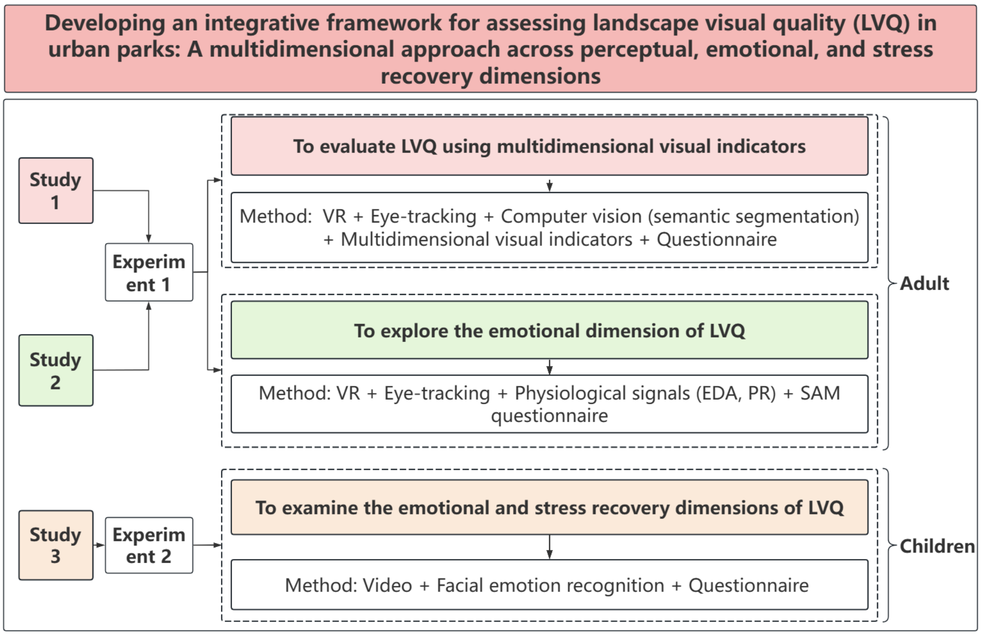

Figure 1.3: Research objectives and methodological framework

Chapter 4: Emotional responses to landscape visual quality This chapter investigates the relationship between LVQ and emotional responses, focusing on how landscape elements influence both visual behavior and emotional responses. By integrating eye-tracking data with physiological and self-reported emotional measures, the study quantifies the emotional impact of landscape elements. The findings contribute to a deeper understanding of how LVQ can be leveraged to enhance emotional well-being in urban parks, providing design recommendations for creating psychologically supportive environments.

Chapter 5: Emotional and stress recovery dimensions of landscape visual quality This chapter extends LVQ research by examining its role in children's emotional and stress recovery. Using facial emotion recognition technology and psychological assessments, the study explores how landscape elements influence children's emotion and stress recovery. This research provides insights into optimizing urban park design to better support children's emotional well-being and stress recovery, ensuring that these spaces are both engaging and psychologically beneficial for younger users.

Chapter 6: Conclusion, implications, and limitations This final chapter synthesizes the key findings on how landscape elements influence human well-being in urban parks. It consolidates these insights to highlight their implications for urban planning and landscape design, demonstrating how LVQ enhancements contribute to more engaging and supportive urban environments. The chapter also discusses key strategies derived from the research, providing actionable recommendations for future urban park development. Additionally, the study's limitations are critically evaluated, addressing methodological challenges and data constraints. Finally, future research directions are outlined, emphasizing the need for further investigations to refine LVQ assessment and explore its broader implications, particularly in rapidly urbanizing regions.

Chapter 2

Literature review

2.1 Landscape visual quality assessment

Landscapes, as products of long-term interaction between humans and nature, have become increasingly complex in function and appearance over time [61]. Human activities have not only influenced the function and appearance of landscapes, but landscapes in turn have impacted humans [62]. In this context, conservation policies in the United States and Europe highlight the need for a rapid response to landscape changes and provide a framework for international cooperation to maintain landscape quality and characteristics [63]. Moreover, with growing concern for environmental issues, natural resources and landscape aesthetics are regarded as important cultural ecological services, further emphasizing the importance of considering LVQ in landscape management and policy-making [64].

LVQ is defined by the interaction between landscape features and their effects on human observers, significantly influencing urban residents' perceptions and satisfaction with their living environment [42]. Since the 1960s, psychological and behavioral methods have been introduced into the standardized assessment of LVQ to support environmental conservation and the protection of national parks and nature reserves [65]. By the 1980s, landscape assessment research began to focus on distinguishing different landscape attributes, emphasizing the core impact of landscape features on assessment outcomes [66]. Years of research evolution have led to four main assessment paradigms: expert assessment [67], psychophysical assessment [68], cognitive assessment [69, 70], and experiential assessment [71]. These paradigms encompass traditional assessment techniques ranging from Scenic Beauty Estimation [18], Analytic Hierarchy Process [72], Semantic Differential [58], to data collection through interviews [73]. Although these traditional methods have been widely applied, they have limitations in the detailed assessment of urban park landscapes, especially when assessment errors occur due to participants' lack of understanding of professional terminology. Therefore, the fundamental issues of how landscapes are perceived and how various landscape elements trigger specific perceptions remain unresolved in human perception prediction models [22]. This often requires more comprehensive and innovative methods to enhance assessment accuracy, ensuring that LVQ assessments can more effectively support environmental management and policy-making. In the fields of urban planning and landscape design, traditional methods of LVQ assessment have primarily relied on site visits and photographic techniques, which are often affected by factors such as terrain, obstacles, and weather conditions [66, 74]. Particularly in the assessment of unbuilt or renovation projects, the limitations of on-site visits can be especially significant [75]. With advancements in technology, VR has demonstrated its value in simulating and assessing spatial environments. Conducted within controlled laboratory settings, VR not only saves costs and enhances efficiency but also allows researchers to isolate and modify various variables to deeply understand how design decisions impact user experience [76]. The use of head-mounted display devices enhances user immersion, making simulated environments more closely resemble the real world and generating data unattainable from field studies [77]. Moreover, recent research has shown that participants' perceptions of real and virtual environments are similar, providing a solid foundation for visual research [78, 79].

The rapid development of computer vision technology in recent years has propelled research on LVQ assessment based on emerging technologies. Researchers evaluate the LVQ of urban parks by performing semantic segmentation on collected photographs of urban vegetation combined with traditional metrics. However, previous studies on the LVQ of urban parks have primarily relied on image segmentation metrics extracted from two-dimensional images [56], while actual spatial perception occurs in three-dimensional space. This has led to an incomplete understanding of real spatial dimensions, limiting the comprehensiveness and accuracy of assessments. To address this issue, researchers create detailed three-dimensional models and perform semantic segmentation of panoramic images to more accurately simulate and analyze the visual quality of landscapes. On the other hand, traditional methods of collecting visual perception data primarily use questionnaires [22], which involve a translation of perception. Initially, individuals observe the landscape with their eyes, then translate these observations into perceptions to fill out a questionnaire. In contrast, eye-tracking technology can directly capture users' observational information. As a physiological measurement method, eye-tracking has been widely applied in fields such as cognitive linguistics, marketing, neuroscience, and urban design [80–83]. This technology measures attention distribution by capturing the fixation points where an individual's gaze pauses, allowing researchers to collect precise data about users' visual attention [84]. Studies have found that most people focus their attention on man-made objects while walking in parks, with street edges being the most visually attractive areas [85,86]. Additionally, eye-tracking can more accurately observe differences in eye movements when viewing urban and natural images during different vegetation periods. Thus, integrating eye-tracking data with cognitive assessment results to evaluate LVQ offers an effective method, overcoming the shortcomings of questionnaire-based approaches.

2.2 Landscape elements on emotions and visual behavior

Emotional experience is increasingly recognized as a central component of urban spatial design. Grounded in theories such as environmental psychology and behavioral architecture, contemporary urban planning emphasizes not only the physical structure of spaces but also their capacity to evoke emotional responses. As urbanization continues to challenge mental and physical health, planners are turning to nature-based solutions to support psychological well-being. Integrating emotionally resonant landscape features into urban parks aligns with global priorities, such as the United Nations' goals for healthy, inclusive, and sustainable cities. Contemporary research incorporates human emotional responses into urban planning to create environments that enhance health and well-being. Predictive models of landscape spatial features have been developed to assess these effects [87], and studies have examined the influence of elements such as plant color on emotions and perceptions [88]. Analyses of social media and streetscape data quantify emotional responses across different scenarios, revealing that areas with more greenery typically exhibit lower negative emotions [89]. Real-time analysis using mobile EEG technology has compared the emotional impacts of walking versus sitting in urban parks, highlighting that walking helps reduce stress while sitting aids in restoring attention [90]. This research emphasizes the importance of emotional health in landscape composition studies. However, there remains a gap in understanding how specific proportions and types of landscape elements within the same type of space affect emotions. This article aims to fill that gap by systematically analyzing the impact of various landscape elements in urban parks, providing a comprehensive understanding to support more effective urban space design.

Emotional evaluation methods are typically categorized into two main types: self-reported assessments and physiological measurements. Self-report tools such as the semantic differential scale, Likert scale, day reconstruction method, and the Self-Assessment Manikin (SAM) [27, 58, 59, 91] are widely used to capture participants' subjective emotional states. Among these, SAM is particularly popular for its efficiency and ease of use. However, self-reports rely on individuals' introspection, which may be influenced by cognitive bias or limited self-awareness, often requiring complementary data sources for validation. Physiological approaches, on the other hand, assess emotional changes through objective indicators such as facial expressions, vocal tone, posture, and biosignals—including electrodermal activity (EDA), electromyography (EMG), electrocardiography (ECG), and others [87,92]. EDA, EMG, and ECG are especially prevalent in emotion recognition studies due to their sensitivity to autonomic nervous system responses [28, 93]. To improve reliability, many studies adopt a multimodal approach, combining self-reported data with physiological signals to gain a more comprehensive understanding of emotional responses.

Human visual perception relies on different regions of the retina—namely the fovea, parafovea, and peripheral vision. The fovea, located at the center of the retina, offers the highest visual acuity and is responsible for precise detail recognition. To achieve clear vision, individuals move their eyes to direct objects of interest into this high-resolution zone. Eye-tracking technology has made it possible to analyze various eye movement types, such as saccades, smooth pursuit, and fixation, each corresponding to different cognitive and perceptual tasks. In landscape research, these eye movements serve as key indicators of visual attention and preference. Studies have shown that specific spatial features—such as openness, vegetation density, or visual contrast—can significantly influence gaze patterns and fixation durations [94]. For example, natural riverbanks in urban settings have been found to alter visual exploration behavior, highlighting the link between landscape features and attentional engagement [52]. Similarly, the proportion of greenery has been shown to affect visual salience and perception outcomes [56]. Comparative studies between urban and natural environments further reveal that spatial composition, degree of urbanization, and design layout can shape both eye movement patterns and related emotional responses [85, 95]. Beyond landscape studies, eye-tracking has been extensively applied across disciplines—including psychology, education, and human-computer interaction—to investigate cognitive processing during tasks such as reading, visual search, and multimedia learning. These applications further validate the method's reliability in capturing attention, processing effort, and user engagement, reinforcing its suitability for analyzing human responses to spatial environments.

Furthermore, the processing of visual information is closely related to emotional responses, as visual cues can trigger emotions primarily encoded in the brain's medial temporal lobe, responsible for emotional processing [96]. Therefore, visual information and emotional responses are related to memory formation and affect psychological states [97]. For instance, observing certain urban environments can influence emotional responses. The presence of water landscapes not only relieves stress but also helps restore attention, enhancing positive emotions [98,99]. Specific visual layouts in urban environments, such as color schemes and spatial arrangements, also impact individuals' emotional states by affecting pupil diameter

[97]. Despite extensive research, the mechanisms by which visual information is captured and processed to trigger emotional responses are not fully understood. The aim is to tackle this challenging issue by utilizing precise eye-tracking data analysis to fill the research gap on how visual information affects emotional states. Given that existing research primarily focuses on direct comparisons between natural and urban environments, there remains a lack of detailed understanding of how visual behavior specifically modulates emotional responses.

2.3 Landscape elements on emotions and stress recovery

In current urban planning and landscape design, there is often insufficient attention to the LVQ of children's activity spaces. Research shows that high-quality urban parks improve children's physical and mental health [100–102]. In the contemporary educational and social landscape, children encounter heightened pressures from academics, societal expectations, and familial strife, which impact their mental and physical health [25,26,103]. Studies have shown that children in urban impoverished areas are at a higher risk of developing emotional disorders such as depression, anxiety, or behavioral issues like ADHD [104]. Barriers such as limited access to green spaces due to logistical challenges exacerbate these problems [105]. Therefore, it is crucial to research and design environments that enhance the LVQ of children's activity spaces. This approach more effectively supports children's psychological and emotional development, providing a healthier and more inclusive growing environment for children. This emphasizes the importance of enhancing visual quality in urban planning and landscape design to improve child well-being.

Urban parks are vital components of urban infrastructure, significantly enhancing environmental sustainability and public well-being, particularly in terms of mental health [106–108]. An increasing body of research explores the link between urban greenery and physical and mental health benefits. Evidence indicates that green spaces not only bolster physical health and social interactions but also provide multifaceted benefits to human health, enhancing well-being [109, 110]. Brief interactions with nature can quickly yield psychological benefits, such as stress relief and improved mood, particularly beneficial for children's emotional and psychological health [100–102]. These natural encounters offer a respite from urban life's demands, improving relaxation and happiness [100]. Besides psychological advantages, green spaces have direct physical health benefits, including reduced blood pressure and heart rate [111]. Although extensive research highlights the positive impacts of urban greenery on children, there is a lack of studies comparing the effectiveness of different landscape types in alleviating children's stress. Few studies have detailed the landscape features that affect children's emotional well-being and stress recovery. This research aims to fill these gaps by exploring how landscape features influence children's stress relief and emotional health.

Children represent a sensitive and vulnerable group that can be challenging to study due to their inability to fully articulate their emotions and stress levels. Traditional research methods such as surveys [102, 112], sampling [104], and observation [105], while direct and convenient, often lack data to analyze children's emotional and stress recovery states effectively. However, advancements in technology, particularly in facial emotion recognition, now make it possible to collect direct emotional data from children themselves. This study intends to use facial emotion recognition technology to investigate the effect of landscape elements on children's stress recovery and emotional regulation. By providing more detailed data support and theoretical exploration, this approach helps to identify and prioritize urban landscape spaces that offer optimal stress recovery for children. These insights can guide urban planning and landscape design to enhance the LVQ of urban spaces, particularly those utilized by children. By identifying which urban park elements most effectively support children's relaxation and recovery, this targeted approach can inform the design of more conducive environments for children's leisure activities, ultimately enhancing the well-being of children in urban settings. This section focuses specifically on children, a group particularly vulnerable to environmental stressors, to explore how landscape elements influence emotional and stress recovery within the broader LVQ framework.

2.4 Research gaps

In the field of urban landscape design and its influence on human well-being, several key research gaps remain unaddressed:

Limitations of single-indicator LVQ assessments: Traditional methods primarily rely on 2D image analysis and subjective surveys focused on spatial feature indicators. While informative, these approaches fail to capture the complexity of visual landscapes and the diversity of user perceptions, resulting in limited accuracy and generalizability of LVQ classification models.

Lack of integration across multiple dimensions: Current evaluations often emphasize perceptual dimensions while overlooking emotional responses and stress recovery. This absence of multidimensional integration restricts a holistic understanding of how LVQ impacts psychological well-being and user experience.

Insufficient analysis of specific landscape elements: Although features like greenery and water are widely studied, finer-grained components—such as herb plants, shrubs, and the spatial layout of water elements—are rarely examined in detail. Their precise roles in shaping visual attention, emotional regulation, and physiological responses remain unclear, limiting their practical application in design.

Adult-centric research bias: Most studies have focused on adults, neglecting the distinct emotional and stress recovery patterns of children. This gap impedes the development of inclusive and restorative landscape strategies that address the needs of younger users.

Geographic and cultural bias in existing studies: Urban landscape studies have largely been conducted in Western contexts, with limited attention to East Asian environments. The lack of culturally contextualized research hinders the development of locally adaptive guidelines, especially in rapidly urbanizing regions like China.

Gaps between research and practical application: Findings from LVQ research often remain theoretical, with few translated into actionable design strategies. The absence of practical, evidence-based guidance limits their impact on real-world urban park planning and design.

Chapter 3

Assessment of landscape visual quality using multidimensional visual indicators

3.1 Introduction

This chapter aims to construct a perceptual evaluation model for the LVQ of urban parks, integrating eye-tracking, image segmentation, and spatial feature indicators. LVQ is defined by the interaction between landscape features and their effects on human observers, significantly influencing urban residents' perceptions and satisfaction with their living environment [42]. This study developed a LVQ classification model based on multidimensional visual indicators, including eye-tracking, image segmentation, and spatial features. The model performs binary classification of positive and negative perceptions across seven dimensions: beauty, comfort, color, complexity, liveliness, greenness, and safety [22, 56, 113–115]. As essential components of urban ecosystems, urban parks play a key role in promoting public health and well-being by relieving psychological stress, supporting physical activity, and fostering social interaction [1]. High-quality parks contribute to improved quality of life and equitable resource distribution. Therefore, early-stage evaluation of their LVQ is critical for guiding planning decisions and mitigating potential social and spatial inequalities. Traditional methods for evaluating LVQ, such as questionnaire surveys or expert on-site assessments, often suffer from subjectivity and are limited by environmental or logistical constraints—especially in areas under construction or renovation [14, 22]. This study addresses these limitations by employing a VR environment to simulate park landscapes under controlled conditions, enabling repeatable and immersive visual assessments [32, 76, 116]. The proposed method integrates multidimensional visual indicators: eye-tracking technology captures participants' visual attention and gaze behavior [60], semantic segmentation extracts salient landscape components, and spatial feature indicators quantify structural attributes of the park environment. Through this framework, we investigate how different visual characteristics influence human perception and how integrated indicators can improve the evaluation of landscape visual quality. We examined the mechanisms by which these multidimensional visual indicators assess human perceptions of urban parks and enhance LVQ. This study aimed to address the following two research questions:

- How is human perception of urban parks correlated with multidimensional visual indicators?
- How well can a perception model integrating multidimensional visual indicators differentiate positive and negative perceptions? Does it perform better than the model using only spatial feature indicators?

3.2 Method

3.2.1 Study area and panoramic image rendering

Study area

This study selected three urban parks located in the northern, central, and southern regions of China, aiming to capture diverse landscape designs and spatial features for exploring the feasibility of using multidimensional visual indicators to assess LVQ (Figure 3.1). This approach provides a basis for investigating how various urban park designs influence human perceptions. Theseurban parks include urban park, community garden, and ecological wetland. With the assistance of the community park audit tool [117], we recorded the spatial features of each urban park after detailing these descriptions to demonstrate their diversity and differences. Labor Park (park A; Chaoyang, Liaoning Province), located in the city center of Chaoyang, where urban parks dominate the urban landscape. Labor Park is characterized by its diverse trails, educational features, and facilities that support various fitness activities, exemplifying the image of a traditional and multifunctional urban park. Platform Park (park B; Wuhan, Hubei Province) is situated in Wuhan, a national central city, where high-density urban spaces are predominantly composed of community gardens. Located in Wuhan's business core area, Platform Park provides spaces for picnicking and relaxation, fountains, and modern children's entertainment facilities, reflecting the qualities of a small urban recreational green space that serves both the local commercial district and residents. Dory Park (park C; Guangzhou, Guangdong Province), located in the important port city of Guangzhou, effectively integrates water elements into its urban park design. Dory Park features natural hills and lawns, basketball courts, a lake, and playground facilities, showcasing the rich ecological and natural experiences of an ecological wetland. This approach provides a basis for investigating how various urban park designs influence human perceptions and facilitated the development of an inclusive model to assess the manner in which

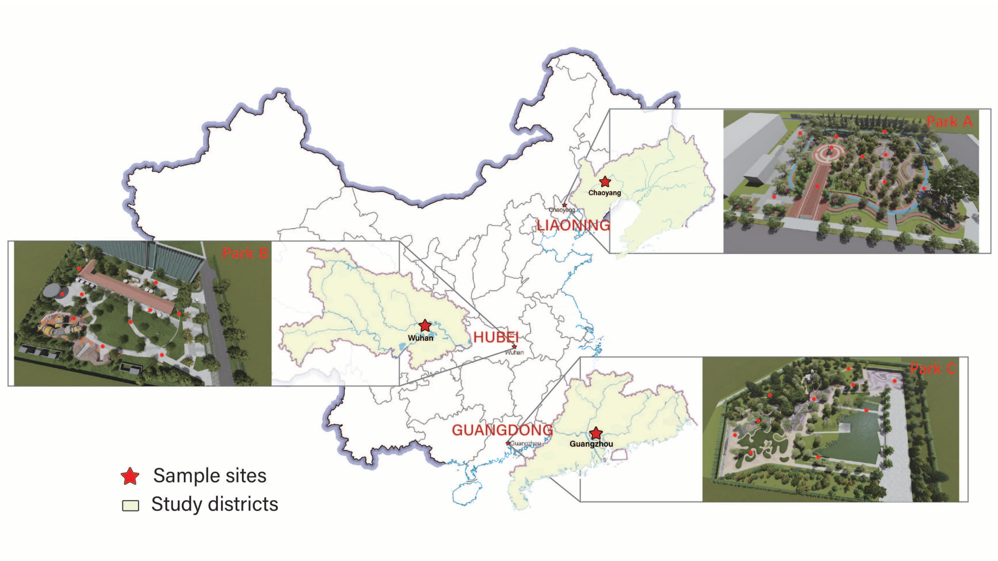

Figure 3.1: Study area and 30 panoramic image-rendering points. Source of base map: standard map service system

the LVQ of urban parks influences human perceptions.

Panoramic image rendering

Technically, we modeled and rendered the three urban parks using SketchUp 2019 (https://www.sketchup.com) and Lumion 10 (https://lumion.com). Panoramic images, produced in JPG format with a resolution of 8192 × 4096 (Figure 3.3), focus specifically on the landscape elements within the urban parks, omitting the surrounding environment and people to solely focus on the urban parks. When rendering panoramic images, we set the sun's azimuth to 38 degrees northeast and the altitude to 60 degrees, simulating a specific time at midday in summer. This setup helps ensure consistency in the rendering conditions of the experimental materials. Ten specific points in each urban park were chosen to ensure complete experiential assessment, culminating in 30 panoramic images (Appendix A). These images were designed to provide participants with a detailed perception of each green space, highlighting the unique landscape elements defining each setting.

3.2.2 Data collection

Overview

The experimental procedure is illustrated in Figure 3.2. Landscape features from various regions were used as variables to assess the human perceptions of urban park LVQ with multidimensional visual indicators. Multidimensional visual indicators to assess LVQ were derived using three approaches. First, eye-

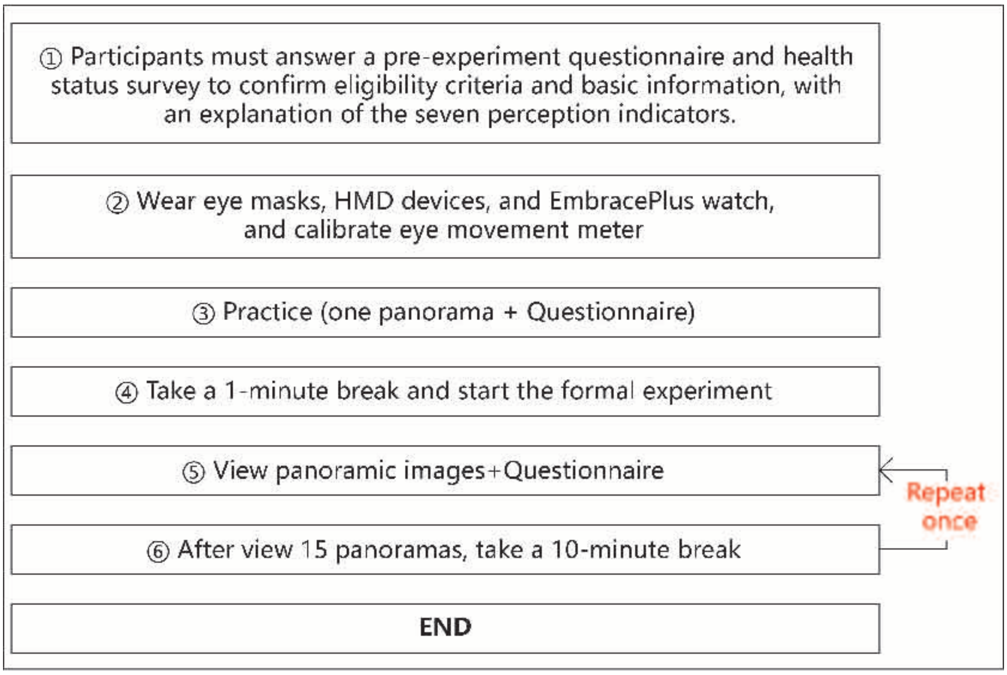

Figure 3.2: Experimental procedure

tracking indicators were derived via visual clustering analysis of user interactions with urban park panoramic images using eye-tracking technology. Second, image segmentation indicators were derived via semantic segmentation of the panoramic images. Third, spatial feature indicators were determined via detailed spatial measurements and calculations. Additionally, to investigate the impacts of landscape features on human emotions and behaviors, emotional data were collected using the self-assessment manikin for psychological responses and EmbracePlus device for physiological data. However, this study mainly focused on multidimensional visual indicators to assess the LVQ of urban parks; emotional data will be analyzed in a study 2.

Eye-tracking indicators

In this study, we used the NeU-VR device developed by FOVE (Tokyo, Japan). The device consists a WQHD OLED (2560×1440) stereo screen and dual infrared eye-tracking systems, achieving a tracking accuracy of 1.15° and frame rate of 120 fps, enabling the smooth recording of eye movements in 360° panorama. The accompanying FOVE Gaze Analyzer software was used to record the eye-tracking data. Various types of eye-tracking data, including time to first fixation, dwell time, fixation ratio, revisit count, first fixation duration, and average fixation duration, were collected. Area of interest (AOI)-based analysis was performed to identify and examine the eye-tracking indicators in the specified regions.

Considering the importance of dwell time and revisit count in understanding visual attention and interest, we mainly focused on these indicators. Dwell time reflects the total accumulated time during which the user's gaze remains on an AOI, indicating the depth of interest in the scene [85]. This indicator is crucial to understand the ways in which long specific landscape elements capture the participants' attention. Revisit count measures the frequency of gaze reentries into an AOI, directly correlating with the user's voluntary focus on specific areas of interest [118]. This indicator helps to identify the elements repeatedly attracting attention, suggesting their importance in the perception of landscapes.

Image segmentation indicators

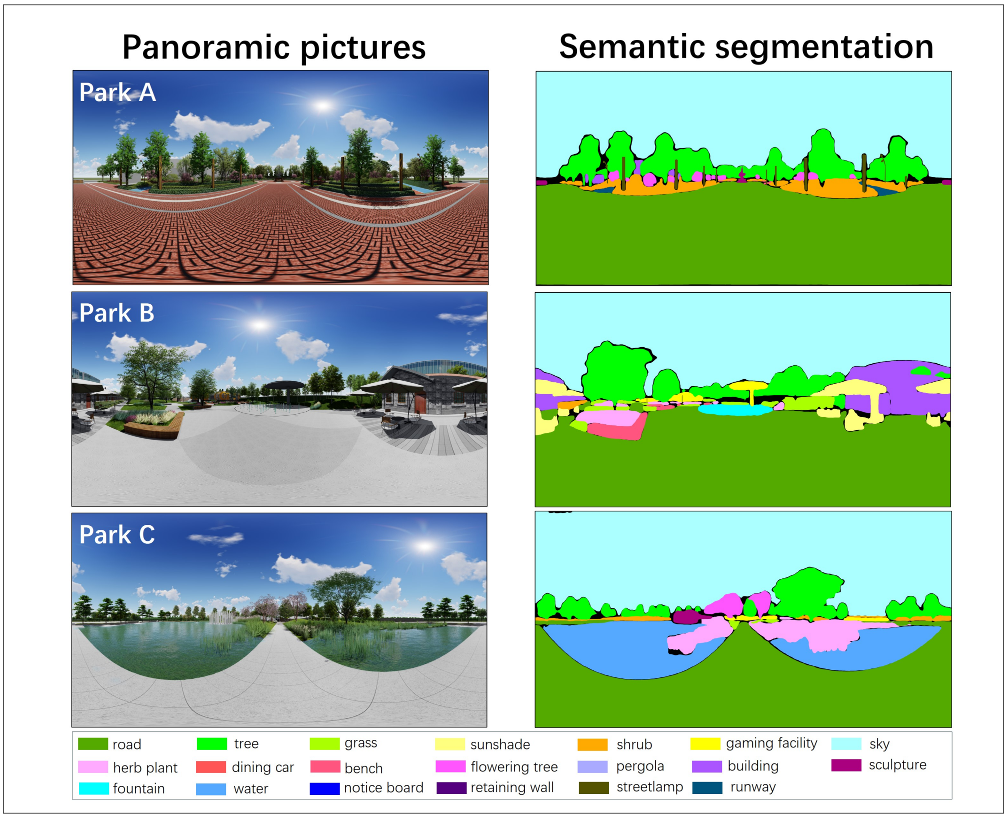

Figure 3.3: Panoramic pictures and semantic segmentation results

To perform precise image semantic segmentation of panoramic photos to calculate the proportions of landscape elements (Figure 3.3), this study used an interactive semi-automatic image annotation tool (ISAT) integrated with the segment-anything model [119]. This tool supports rapid and low-resource image segmentation, adapts to various requirements, and enables semiautomatic annotation using point and bounding box inputs. Additionally, it supports various annotation styles and is compatible with multiple export formats, facilitating integration with different machine learning workflows. Panoramas were first segmented into different color classes representing various landscape features using the aforementioned tools for landscape element analysis. Subsequently, we developed and executed Python scripts using PyCharm Community Edition 2023.2.1 to read the annotated image files, calculate the total pixel count, identify unique colors, and compute each color area's pixel count and proportion, enabling precise quantification of the landscape elements (Appendix B). To ensure the reliability of the segmentation results, we conducted an accuracy evaluation by comparing the ISAT tool-assisted semantic segmentation results with manually segmented results using Adobe Photoshop 2021 (Adobe Inc., San Jose, CA, USA). The average performance of the tool-assisted segmentation method across these metrics was as follows: accuracy of 96.07%, precision of 98.04%, recall of 98.04%, F1 score of 0.98, and Intersection over Union of 0.96. The segmentation results demonstrated strong performance across all metrics, with high reliability and consistency.

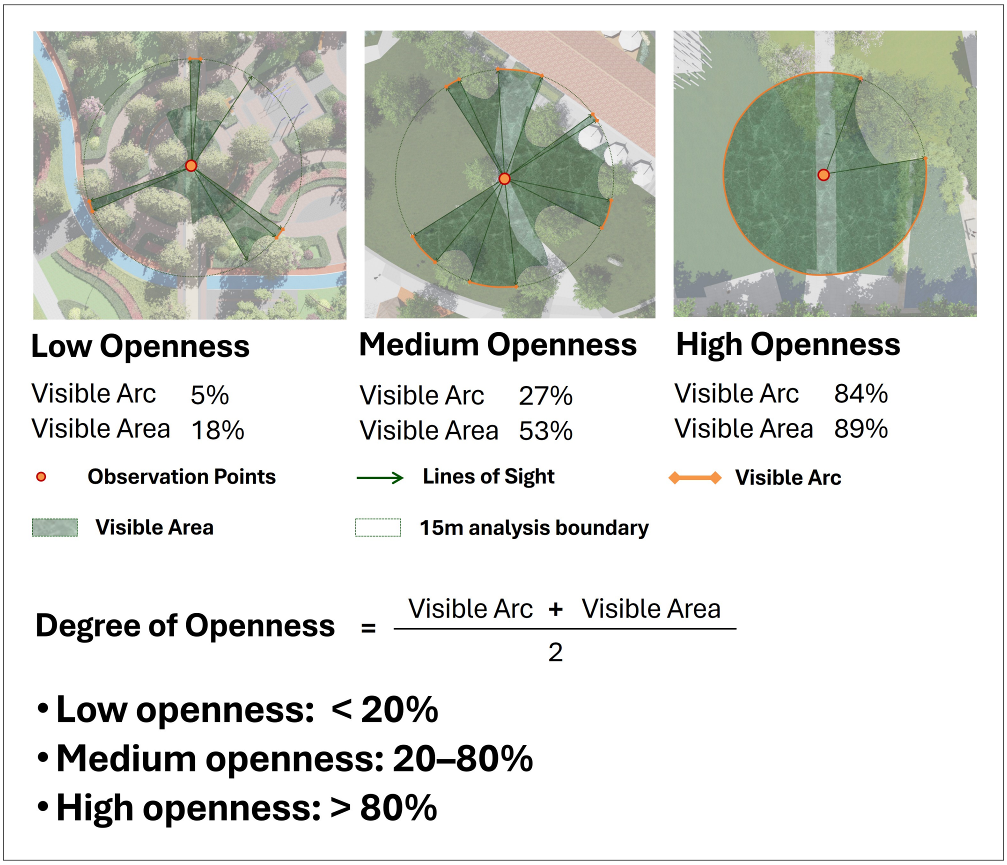

Figure 3.4: Degree of openness calculation method

Spatial feature indicators

Visual perception is a primary source of information for assessing landscape quality, influenced by spatial layout and landscape features such as shape, depth, color, and dynamics [120]. These elements underscore the necessity of focusing on specific spatial features that most significantly impact visual quality, leading to the selection of four key indicators: PlantingStyle, DegreeOfOpenness, ContrastDegree, and Topography. PlantingStyle, defined as the arrangement of trees, influences the aesthetic experience by creating visually pleasing silhouettes that shape the visual aesthetics of greenspaces [121]. Trees are categorized as isolated, linear, or clustered based on their arrangements. DegreeOfOpenness relates to the sense of enclosure or exposure, affecting overall perception [122,123]. Following the studies [124, 125], we used AutoCAD 2019 (developed by Autodesk, San Rafael, California, USA) to calculate the field of view openness within a 15-meter radius from a fixed point by measuring the visible arc length and horizontal area size (Figure 3.4). ContrastDegree, highlighting the color differences among landscape elements, impacts aesthetic perception and preference. We classified contrast as low, medium, or high based on color differences between major landscape elements. Lastly, Topography which describes the shape and features of the ground influences the visual scale of landscapes, thereby enriching the visual experience [126]. These classifications include no topography, partial topography, or complete topography. We identified 18 quantitative indicators, which were divided into two categories: nine image segmentation indicators (CrownCoverage, ArtificialObjects, SkyRatio, GreenRatio, FlowerRatio, FlowerTreeRatio, HerbRatio, RoadRatio, and WaterRatio) and nine spatial feature indicators (EdgeWidth, EdgeLayers, ArborSpecies, ShrubSpecies, HerbSpecies, PlantRichness, NumberOfElements, NumberOfMaterials, and SpaceTypeCategories). Additionally, four qualitative indicators, involving spatial feature indicators (PlantingStyle, DegreeOfOpenness, ContrastDegree, and Topography), were identified. Together, these 22 indicators comprehensively described the landscape features, as detailed in Table 3.1.

Table 3.1: Spatial feature and image segmentation indicators.

Indicators	English name	Feature element calculation
Qualitative indicators		
Spatial feature Indicators	PlantingStyle [22]	Describes the way trees are planted. Isolated signifies a single tree as the main view. Linear signifies rows or columns of trees. Clustered signifies more than two rows or columns of trees. Isolated=1, Linear=2, and Clustered=3
	DegreeOfOpenness [124]	Describes the visual and mobility permeability of an area. Low openness indicates a visible arc length and visible horizontal area $< 20\%$, high openness indicates a visible arc length and visible horizontal area $> 80\%$, medium openness indicates a visible arc length and visible horizontal area between the two at 20–80%. Low=1, Medium=2, and High=3
	ContrastDegree [22]	Describes the color differences between landscape elements. High color contrast indicates a large color difference, such as red and green. Low color contrast indicates a small color difference, such as green and white. Medium color contrast indicates a noticeable color difference that is not too strong, such as green and yellow. Low color contrast=1, Medium color contrast =2, and High color contrast=3.
	Topography [66]	Describes the shape and features of the ground. No topography indicates that the surface is essentially flat with no significant topographic features. Partial topography indicates that topographic features are present in certain areas of the scene but are not dominant across space. Complete topography indicates that significant topographic structures dominate space. No topography=1, Partial topography=2, and Complete topography=3.
Quantitative Indicators		
	EdgeWidth [87]	EdgeWidth = Ds-Dh, where Ds is the distance from the refer-ence point (a point where a person stands on the road) to the soft boundary, and Dh is the distance from the same reference point to the hard boundary

Continued on next page

Table 3.1 – continued from previous page

Indicators	English name	Feature element calculation
Spatial Features Indicators	EdgeLayers [22]	EdgeLayers = Number of soft boundary layers on both sides of the road (e.g., lawns, flower beds, and small shrubs)
	ArborSpecies [22]	ArborSpecies = Number of tree species
	ShrubSpecies [22]	ShrubSpecies = Number of shrub species
	HerbSpecies [22]	HerbSpecies = Number of herb species
	PlantRichness [22]	PlantRichness = NAS+NSS+NHS, where NAS is the number of arbor/tree species, NSS is the number of shrub species; and NHS is the number of herb species
	NumberOfElements [87]	Number of landscape elements
	NumberOfMaterials [87]	Number of spatial materials
	SpaceTypeCategories [87]	Number of different space types
Image Segmentation Indicators	CrownCoverage	CrownCoverage = CCA/PIA×100%, where CCA (crown coverage area) is the area of the tree canopy, and PIA (panoramic image area) is the total area of the panoramic picture
	ArtificialObjects	ArtificialObjects = AOA/PIA×100%, where AOA (artificial object area) is the area of the artificial objects, and PIA (panoramic image area) is the total area of the panoramic picture
	SkyRatio	SkyRatio = SA/PIA×100%, where SA (sky area) is the area of the sky, and PIA (panoramic image area) is the total area of the panoramic picture
	GreenRatio	GreenRatio = GA/PIA×100%, where GA (green area) is the area of the green region, and PIA (panoramic image area) is the total area of the panoramic picture
	FlowerRatio	FlowerRatio = FA/PIA×100%, where FA (flower area) is the area of the flower, and PIA (panoramic image area) is the total area of the panoramic picture

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Table 3.1 – continued from previous page

Indicators	English name	Feature element calculation
	FlowerTreeRatio	FlowerTreeRatio = FTA/PIA×100%, where FTA (flower tree area) is the area of the flower tree, and PIA (panoramic image area) is the total area of the panoramic picture
	HerbRatio	HerbRatio = HA/PIA×100%, where HA (herb area) is the area of the herb, and PIA (panoramic image area) is the total area of the panoramic picture
	RoadRatio	RoadRatio = RA/ PIA×100%, where RA (road area) is the area of the road, and PIA (panoramic image area) is the total area of the panoramic picture
	WaterRatio	WaterRatio = WA/PIA×100%, where WA (water area) is the area of the water, and PIA (panoramic image area) is the total area of the panoramic picture

Perception questionnaire survey

In this study, participants evaluated each photograph according to seven perceptual dimensions: beauty, color, comfort, complexity, liveliness, greenness, and safety [22,56,113–115], as detailed in Table 3.2. Beauty captures the aesthetic appeal of the urban park landscape, commonly used to assess LVQ and reflect public aesthetic preferences [22, 127–129]. Comfort replaces the previously used indicator depression to better reflect the positive psychological benefits of urban parks [113]. Comfort captures the sense of relaxation and mental ease experienced in urban park. It reflects the restorative effect of the environment, helping to reduce mental fatigue and promote relaxation [130, 131]. Color captures the diversity of colors within the urban park. Different combinations of colors reflect the richness of the environment, influencing individuals' preferences and viewing behaviors [22]. Complexity captures the richness of landscape elements and materials within the urban park, enhancing the visual interest and engagement of the environment [22,132]. Liveliness captures the vitality of spatial and landscape elements within the urban parks, reflecting the inherent human connection to natural environments and the preference for spaces that are vibrant and full of life [133, 134]. Greenness is newly added to capture the presence and density of vegetation within the urban parks, a vital aspect for assessing the visual attractiveness of urban parks [56]. Safety captures the perceived safety based on visibility and spatial layout of the urban park. The spatial configuration and physical characteristics of landscape features can significantly influence people's sense of safety [22, 124, 135]. After experiencing each panoramic image, the participants used a 9-point Likert scale (e.g., "This landscape feels beautiful": -4 [strongly disagree] to 4 [strongly agree]) to rate the image on multiple dimensions: beauty, comfort, color, complexity, liveliness, greenness, and safety. It is important to note that despite clearly distinguishing each perception indicator during the questionnaire design, some overlap in participant responses may still occur. Prior to the experiment, each participant was thoroughly briefed on the definitions of each indicator to minimize confusion and enhance the reliability of their responses.

Table 3.2: Description and question of human perception indexes

Index	Definition	Questions corresponding to the questionnaire
Beauty	Indicates the aesthetic appeal of the urban park landscape.	This landscape feels beautiful
Comfort	Indicates the sense of relaxation and mental ease experienced in the urban park.	This landscape feels comfortable
Color	Indicates the diversity of colors within the urban park.	This landscape feels colorful
Complexity	Indicates the richness of landscape elements and materials within the urban park.	This landscape feels complex
Liveliness	Indicates the vitality of spatial and landscape elements within the urban park.	This landscape feels lively
Greenness	Indicates the presence and density of vegetation within the urban park.	This landscape's degree of greenness
Safety	Indicates the perceived safety based on visibility and spatial layout of the urban park.	This landscape's degree of safety

Participants

Sixty Chinese nationals were recruited from the Japan Advanced Institute of Science and Technology Graduate School (Nomi, Japan) to ensure a culturally relevant perspective aligned with the background of the urban parks represented in this study. All students were healthy, aged 20–29 (41), 30–39 (16), and 40–49 (3) years, with an equal gender distribution (30 males and 30 females) from diverse academic backgrounds. Before the experiment, all participants were informed about the procedures, risks, and confidentiality issues and signed informed consent forms. The study adhered to the principles of the Declaration of Helsinki. To mitigate adverse effects, such as dizziness, nausea (VR sickness), and fatigue from prolonged exposure to head-mounted displays, participants took a 10-min break after every 15 panoramic images. Participants were seated comfortably in swivel chairs and wore NeU-VR headsets to immerse themselves in the ms. The order of the 30 panoramic images from the three urban parks was randomly assigned to avoid order effects on the output. The participants viewed each panoramic image for 1 min. After observing each panoramic image, the participants rated it on several dimensions using the 9-point Likert scale. Each experiment lasted for 1 h 30 min. Participants received 1500 Japanese Yen for their participation in the study.

3.2.3 Data analysis

1. Pre-selection of indicators

FOVE Gaze Analyzer (FOVE) was used to analyze the eye-tracking data. Normality tests conducted using IBM SPSS Statistics 29.0.0.0 (IBM, New York, NY, USA) revealed that most variables, including questionnaire responses, eye-tracking data, and quantitative and qualitative data, were not normally distributed. Spearman's correlation analysis was used to explore the relationship between eye-tracking data, quantitative data, and human perception. Additionally, Welch's one-way analysis of variance was used to analyze the significant differences in human perception based on qualitative data, facilitating the elimination of irrelevant indicators for subsequent generalized estimating equations logistic regression analysis.

2. Perception data reclassification and generalized estimating equations logistic regression

This study collected a total of 12,600 data points from 60 participants, each of whom evaluated 30 panoramic urban park images across seven perceptual dimensions. Seven human perceptions served as dependent variables, with eye-tracking, image segmentation, and spatial feature indicators acting as independent variables in the perception model. Binary reclassification method: This method processes all human perceptions with the aim of reducing instability and uncertainty in human perception assessments, especially near the middle values [136, 137].For example, beauty perception is classified as: yes=1 (beauty perception_1, equal to and higher than the average value) and no=0 (beauty perception_0, below the average value). The reclassified value q_{ij} can be represented by equation (3.1):

$$q_{ij} = \begin{cases} 1, & \text{if } Q_{ij} \geq \overline{Q}_j \\ 0, & \text{if } Q_{ij} < \overline{Q}_j \end{cases} \tag{3.1}$$

q_{ij} is the reclassified value, Q_{ij} is the original score of the photo, i represents the photo number, j represents a certain perception, and $\overline{Q}_j$ is the average score of the j-th perception.

To clarify the correlations between various factors and human perceptions, stepwise regression was performed to select and simplify the variables, guided by the smallest Akaike information criterion (AIC) values [22]. Multicollinearity was assessed during this process using variance inflation factor (VIF) values to ensure the stability of the model. VIF = 1 indicated no multicollinearity, values = 1–4 indicated low multicollinearity, values > 4 indicated moderate multicollinearity, and values > 10 indicated high multicollinearity. VIF values exceeding the critical threshold were addressed by further refining the variables. Given the clustered nature of the data, generalized estimating equations (GEE) logistic regression was employed to construct the final perceptual models. Quasi-likelihood under the independence model criterion (QIC) values were calculated to assess the model fit and guide model selection. By accounting for within-participant correlations arising from repeated evaluations of multiple urban park images, GEE provided a reliable framework to analyze the relationships between predictor variables and outcomes effectively addressing the dependencies inherent in clustered data [138–140].

3. Visualization and performance evaluation of perception models

Error bar plots were employed as graphical tools to visualize the relationships between predictor variables and human perceptions of urban park, providing an intuitive and effective means of interpreting the results from the GEE logistic regression models. We assessed the performance of the perception model using the receiver operating characteristic (ROC) curve and area under the curve (AUC) method [141,142]. An ROC curve closer to the top left corner and AUC value closer to 1.0 typically indicate good model performance. Specifically, AUC quantifies the model's ability to distinguish between positive and negative perceptions, with higher values indicating greater discriminatory power. Sensitivity and specificity indicated the model's ability to identify positive and negative perceptions of urban park correctly. Threshold value indicated the critical point for differentiating between positive and negative perceptions. The data analysis and visualization processes were implemented using RStudio 4.3.3 (developed by Posit, Boston, Massachusetts, USA) [143].

3.3 Results

3.3.1 Pre-selection of multidimensional visual indicators

(1) Correlation of image segmentation indicators with landscape visual quality

Analyzing the correlations between different perceptual and image segmentation indicators (Figure 3.5, Table 3.3), the image segmentation indicators for water ratio ($p < 0.01$), herb ratio ($p < 0.01$), and flower ratio ($p < 0.01$) all show significant positive correlations with beauty, indicating they have a notable positive impact on the perception of beauty. Water ratio ($p < 0.01$) and flower ratio ($p < 0.05$) are positively correlated with comfort, having a significant positive influence. Flower ratio ($p < 0.01$) is also positively correlated with color, suggesting that an increase in flower ratio positively affects color perception. Herb ratio ($p < 0.01$) and flower ratio ($p < 0.01$) are positively correlated with complexity, indicating they have a notable positive impact on the perception of complexity. Herb ratio ($p < 0.01$) and flower ratio ($p < 0.05$) are positively correlated with liveliness, significantly enhancing the perceived liveliness of the landscape. Green ratio ($p < 0.01$) and crown coverage ($p < 0.01$) are positively correlated with the greenness of the landscape, while sky ratio ($p < 0.05$), road ratio ($p < 0.01$), and artificial objects ($p < 0.01$) are negatively correlated. There is no significant correlation between safety perception and the image segmentation indicators.

(2) Correlation of spatial feature indicators with landscape visual quality

Spatial feature indicators relate to human perceptions of spatial dimensions, features, colors, and more (Figure 3.6, Table 3.3). The spatial feature indicators affecting the perception of beauty are herb species ($p < 0.01$), number of elements ($p < 0.01$), and number of materials ($p < 0.01$); as these indicators increase, the perception of beauty also increases. Beauty perception is negatively correlated with shrub species ($p < 0.05$), with an increase in shrub species leading to a decrease in beauty perception. The spatial feature indicators affecting comfort are herb species ($p < 0.05$), number of elements ($p < 0.01$), number of materials ($p < 0.05$), and planting style ($p < 0.05$); comfort increases as these indicators rise. The spatial feature indicators affecting color perception are the number of elements ($p < 0.05$), number of materials ($p < 0.01$), degree of contrast ($p < 0.05$), and planting style ($p < 0.01$); these indicators are positively correlated with color perception. The spatial feature indicators affecting complexity perception are herb species ($p < 0.01$), number of elements ($p < 0.01$), number of materials ($p < 0.01$),

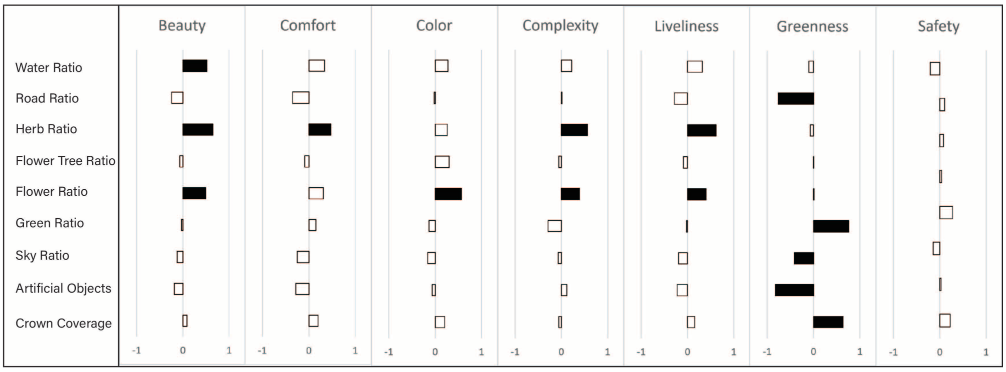


Figure 3.5: The relationship between 9 image segmentation indicators and 7 human perceptions. The black bars indicate that the feature indicators significantly explain the LVQ indicators, with the X axis representing the F values (for qualitative indicators) and the Cor values (n = 30)

and degree of contrast ($p < 0.05$); these indicators are positively correlated with complexity. The spatial feature indicators affecting liveliness perception are herb species ($p < 0.01$), number of elements ($p < 0.01$), and number of materials ($p < 0.01$); as these indicators increase, liveliness perception increases. Conversely, liveliness perception is negatively correlated with shrub species ($p < 0.05$), with an increase in shrub species leading to a decrease in liveliness perception. Greenness perception is positively correlated with the degree of openness ($p < 0.05$); as openness increases, the perception of greenness decreases. Safety perception is only positively correlated with space type categories ($p < 0.05$).

Based on the correlation analysis of qualitative and quantitative indicators, we classify the landscape feature elements according to image segmentation and spatial feature indicators and summarize the correlation between image segmentation indicators and spatial feature indicators and perceptual evaluation (Table 3.3). Edge width, edge layers, arbor species, plant richness, flowering tree ratio, and topography, these six indicators were not correlated with any perception evaluation and therefore were excluded.

(3) Correlation of eye-tracking indicators with landscape visual quality

Before analysis, the dwell time and the revisit count were calculated for each individual element for all participants. Spearman correlation analysis was applied to the eye-tracking data and the questionnaire data. In dwell time (Figure 3.7), herb plants ($p < 0.01$) and water landscape ($p < 0.01$) showed a strong positive correlation with beauty, liveliness, comfort, and complex. Among these, shrubs ($p < 0.01$) showed a significant negative correlation with complex. Artificial objects ($p < 0.01$) showed a very strong negative correlation with greenness.

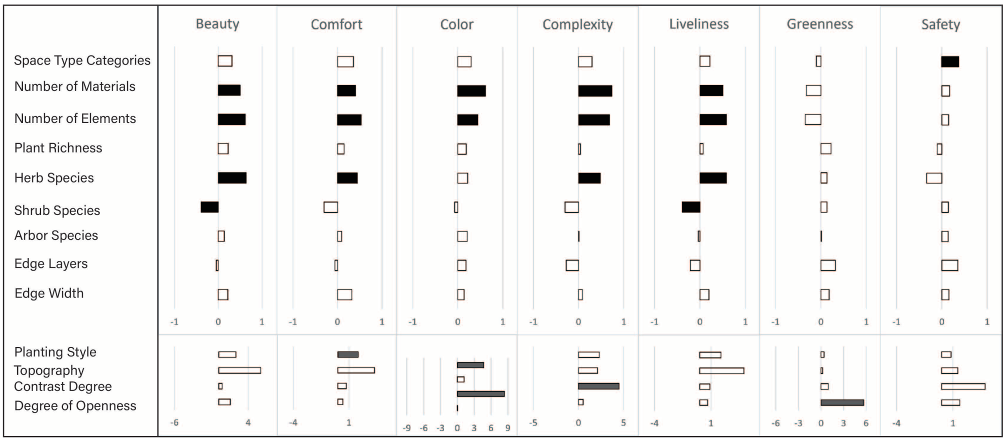


Figure 3.6: The relationship between 13 spatial feature indicators and 7 human perceptions (n = 30)

Table 3.3: Summary of correlations between image segmentation and spatial feature indicators with human perception

Aspect	**Image segmentation indicators**	**Spatial feature indicators**
Beauty	WaterRatio (+), HerbRatio (+), FlowerRatio (+)	HerbSpecies (+), NumberOfElements (+), NumberOfMaterials (+), ShrubSpecies (-)
Comfort	FlowerRatio (+), WaterRatio (+)	HerbSpecies (+), NumberOfElements (+), NumberOfMaterials (+), PlantingStyle (+)
Color	FlowerRatio (+)	NumberOfElements (+), ContrastDegree (+), NumberOfMaterials (+), PlantingStyle (+)
Complexity	HerbRatio (+), FlowerRatio (+)	HerbSpecies (+), NumberOfElements (+), NumberOfMaterials (+), ContrastDegree (+)
Liveliness	HerbRatio (+), FlowerRatio (+)	HerbSpecies (+), NumberOfElements (+), NumberOfMaterials (+), ShrubSpecies (-)
Greenness	GreenRatio (+), CrownCoverage (+), SkyRatio (-), RoadRatio (-), ArtificialObjects (-)	DegreeOfOpenness (+)
Safety	None	SpaceTypeCategories (+)

Note: (+) represents positive correlation; (-) represents negative correlation.

Similar to dwell time, the revisit count (Figure 3.7) for herb plants ($p < 0.01$) and water landscape($p < 0.01$) showed positive correlations with perceptions of beauty, liveliness, comfort, and complexity. The revisit count for shrubs ($p < 0.01$) showed a significant negative correlation with perceptions of comfort and complexity. Grass ($p < 0.05$) showed a significant negative correlation with color.

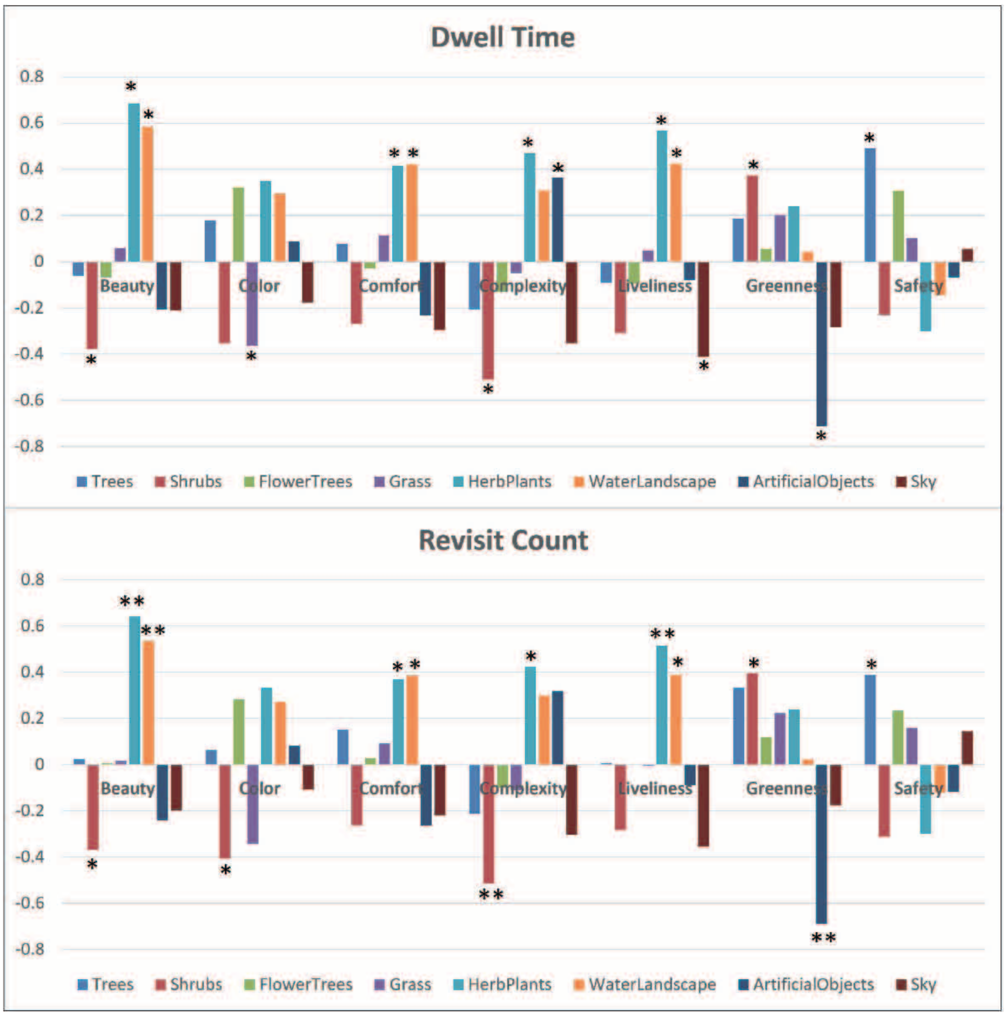


Figure 3.7: Correlation coefficients between landscape perception evaluation and eye-tracking data

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

Indicators showing significant correlations were used for subsequent analysis.

3.3.2 Perceptual model construction and visualization

We first assessed the performance of the perception models using the ROC and AUC method (Figure 3.8) to quantify their accuracy in distinguishing between positive and negative perceptions. Error bar plots, as shown in Figure 3.9, were employed to visualize the estimated coefficients and their 95% confidence intervals from the GEE logistic regression models.

Final QIC for beauty GEE logistic regression analysis was 1871.82 (Table 3.4). ROC curve for the model had an AUC of 0.82 (Figure 3.8a). Error bar plots for beauty perception (Figure 3.9a) show that NumberOfElements had the highest standardized coefficient. ArtificialObjects was the most prominent negative indicator, whereas NumberOfElements was the most significant positive indicator affecting the perception of beauty.

Table 3.4: Final GEE logistic regression beauty perceptual model variables (QIC = 1871.82)

Variable	Estimate	Std.Error	p value	95 % CI
(Intercept)	0.81	0.29	< 0.01	(0.239, 1.389)
DTHerbPlants	0.09	0.02	< 0.01	(0.047, 0.125)
NumberOfElements	0.46	0.03	< 0.01	(0.394, 0.528)
SkyRatio	–8.45	0.96	< 0.01	(–10.330, –6.563)
ArtificialObjects	–6.13	0.68	< 0.01	(–7.457, –4.806)
WaterRatio	27.67	5.82	< 0.01	(16.270, 39.072)
DegreeOfOpenness_Medium	0.44	0.14	< 0.01	(0.156, 0.717)

Final QIC for comfort GEE logistic regression analysis was 2158.92 (Table 3.5). ROC curve for the model exhibited an AUC of 0.74 (Figure 3.8b). Error bar plots for comfort perception (Figure 7b) show that NumberOfElements had the highest standardized coefficient. RoadRatio was the most prominent negative indicator, whereas NumberOfElements was the most significant positive indicator affecting the perception of comfort.

Final QIC for color GEE logistic regression analysis was (Table 3.6). ROC curve for the model exhibited an AUC of 0.74 (Figure 3.8c). Error bar plots for color perception (Figure 3.9c) show that ContrastDegree_High had the highest standardized coefficient. RCGrass was the most prominent negative indicator, whereas ContrastDegree_High was the most significant positive indicator affecting the perception of color.

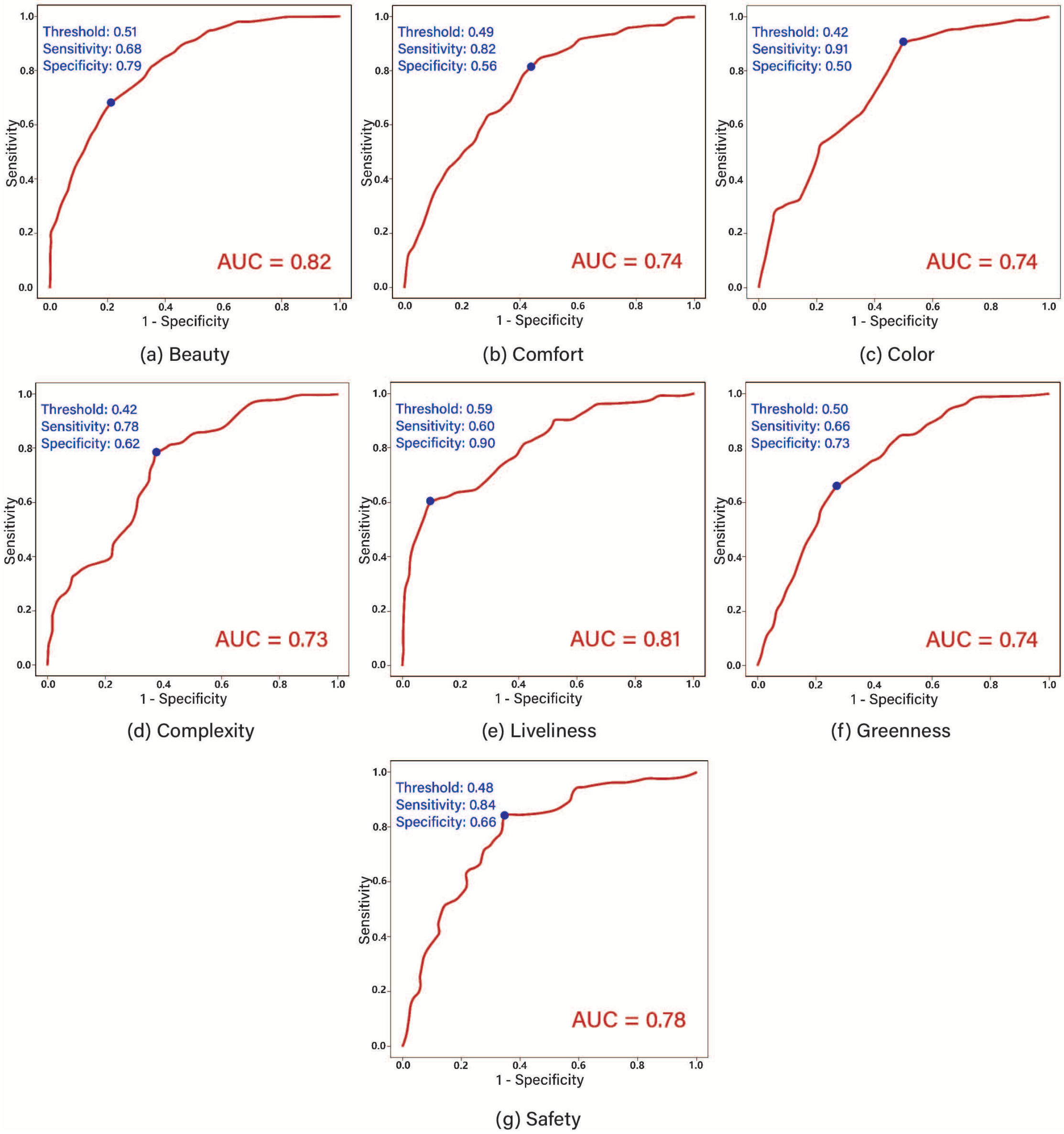
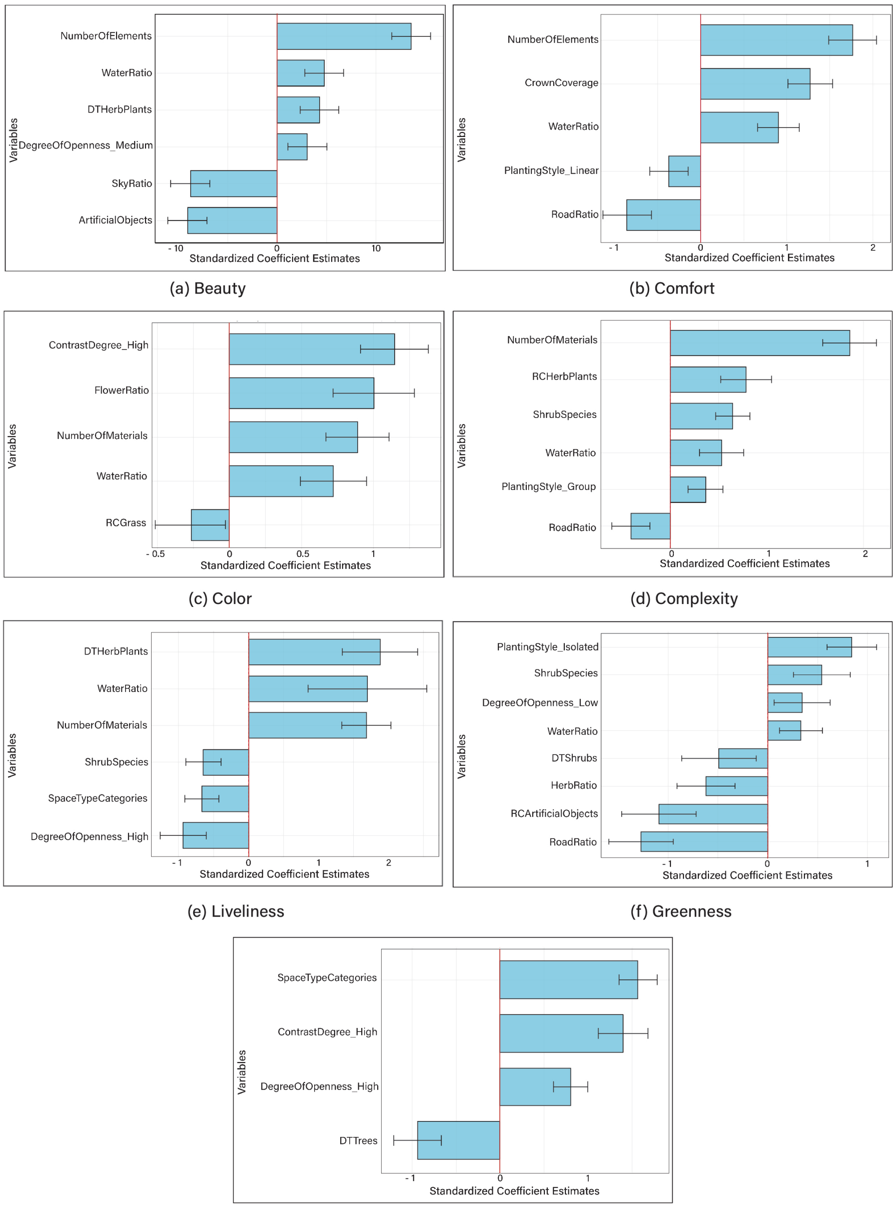


Figure 3.8: ROC curve of the seven human perceptions, (a) beauty, (b) comfort, (c) color, (d) complexity, (e) liveliness, (f) greenness, and (g) safety, based on GEE logistic regression analysis



(a) Beauty

(b) Comfort

(c) Color

(d) Complexity

(e) Liveliness

(f) Greenness

(g) Safety

Figure 3.9: Error bar plots of the seven human perceptions: (a) Beauty, (b) Comfort, (c) Color, (d) Complexity, (e) Liveliness, (f) Greenness, and (g) Safety, showing standardized coefficients with 95% confidence intervals from GEE logistic regression analysis

Table 3.5: Final GEE logistic regression comfort perceptual model variables (QIC = 2158.92)

Variable	Estimate	Std.Error	p value	95 % CI
(Intercept)	–2.46	0.30	< 0.01	(–3.048,–1.872)
NumberOfElements	0.38	0.03	< 0.01	(0.322, 0.444)
CrownCoverage	7.81	0.81	< 0.01	(6.225, 9.391)
RoadRatio	–4.14	0.71	< 0.01	(–5.522, –2.755)
WaterRatio	20.163	2.77	< 0.01	(14.736, 25.591)
PlantingStyle_Linear	–0.39	0.12	< 0.01	(–0.628, –0.158)

Table 3.6: Final GEE logistic regression color perceptual model variables (QIC = 2117.28)

Variable	Estimate	Std.Error	p value	95 % CI
(Intercept)	-2.52	0.22	< 0.01	(–2.956, –2.092)
RCGrass	–0.17	0.08	< 0.05	(–0.331, –0.007)
NumberOfMaterials	0.11	0.01	< 0.01	(0.084, 0.139)
WaterRatio	16.11	2.60	< 0.01	(11.011, 21.201)
FlowerRatio	6.74	0.97	< 0.01	(4.840, 8.630)
ContrastDegree_High	1.16	0.12	< 0.01	(0.920, 1.392)

Final QIC for complexity GEE logistic regression analysis was 2147.22 (Table 3.7). ROC curve for the model exhibited an AUC of 0.73 (Figure 3.8d). Error bar plots for complexity perception (Figure 3.9d) show that NumberOfMaterials had the highest standardized coefficient. RoadRatio was the most prominent negative indicator, whereas NumberOfMaterials was the most significant positive indicator affecting the perception of complexity.

Table 3.7: Final GEE logistic regression complexity perceptual model variables (QIC = 2147.22)

Variable	Estimate	Std.Error	p value	95 % CI
(Intercept)	-3.76	0.31	< 0.01	(–4.363, –3.150)
RCHerbPlants	0.21	0.04	< 0.01	(0.141, 0.283)
ShrubSpecies	0.21	0.03	< 0.01	(0.149, 0.262)
NumberOfMaterials	0.23	0.02	< 0.01	(0.198, 0.267)
RoadRatio	–1.95	0.48	< 0.01	(–2.894, –1.002)
WaterRatio	11.85	2.58	< 0.01	(6.792, 16.906)
PlantingStyle_Group	0.37	0.09	< 0.01	(0.185, 0.545)

Final QIC for liveliness GEE logistic regression analysis was 1864.32 (Table 3.8). ROC curve for the model exhibited an AUC of 0.81 (Figure 3.8e). Error bar plots for liveliness perception (Figure 3.9e) show that DTHerbPlants had the highest standardized coefficient. DegreeOfOpenness_High was the most prominent negative indicator, whereas DTHerbPlants was the most significant positive indicator affecting the perception of liveliness.

Final QIC for greenness GEE logistic regression analysis was 2160.98 (Table 3.9). ROC curve for the model exhibited an AUC of 0.74 (Figure 3.8f). Error bar plots for the perception of greenness (Figure 3.9f) show that RoadRatio had the highest standardized coefficient. RoadRatio was the most prominent negative indicator, whereas PlantingStyle_Isolated was the most significant positive indicator affecting the perception of greenness.

Table 3.8: Final GEE logistic regression liveliness perceptual model variables (QIC = 1864.32).

Variable	Estimate	Std.Error	p value	95 % CI
(Intercept)	-2.02	0.30	$<$ 0.01	(–2.620, –1.429)
DTHerbPlants	0.14	0.02	$<$ 0.01	(0.101, 0.183)
ShrubSpecies	–0.21	0.04	$<$ 0.01	(–0.285, –0.126)
NumberOfMaterials	0.21	0.02	$<$ 0.01	(0.167, 0.255)
SpaceTypeCategories	–0.28	0.05	$<$ 0.01	(–0.381, –0.178)
WaterRatio	37.82	9.61	$<$ 0.01	(18.982, 56.655)
DegreeOfOpenness_High	–1.25	0.23	$<$ 0.01	(–1.689, –0.808)

Table 3.9: Final GEE logistic regression greenness perceptual model variables (QIC = 2160.98).

Variable	Estimate	Std.Error	p value	95 % CI
(Intercept)	3.45	0.49	$<$ 0.01	(1.935, 3.395)
DTShrubs	-5.45	0.96	$<$ 0.01	(–0.045, –0.006)
RCArtificialObjects	-0.09	0.03	$<$ 0.01	(–0.291, –0.142)
ShrubSpecies	0.60	0.19	$<$ 0.01	(0.082, 0.263)
RoadRatio	-3.30	1.03	$<$ 0.01	(–7.665, –4.549)
WaterRatio	0.18	0.06	$<$ 0.01	(2.599, 12.186)
HerbRatio	0.13	0.05	$<$ 0.01	(–6.055, –2.178)
DegreeOfOpenness_Low	-0.59	0.21	$<$ 0.05	(0.069, 0.705)
PlantingStyle_Isolated	0.11	0.06	$<$ 0.01	(0.874, 1.600)

Final QIC for safety GEE logistic regression analysis was 2076.22 (Table 3.10).

ROC curve for the model exhibited an AUC of 0.78 (Figure 3.8g). Error bar plots for safety perception (Figure 3.9g) show that SpaceTypeCategories had the highest standardized coefficient. DTTree was the most prominent negative indicator, whereas SpaceTypeCategories was the most significant positive indicator affecting the perception of safety.

Table 3.10: Final GEE logistic regression safety perceptual model variables (QIC = 2076.22)

Variable	Estimate	Std.Error	p value	95 % CI
(Intercept)	–2.49	0.21	< 0.01	(–2.899, –2.09)
DTTrees	–0.05	0.01	< 0.01	(–0.065, –0.036)
SpaceTypeCategories	0.66	0.05	< 0.01	(0.566, 0.748)
DegreeOfOpenness_High	1.07	0.13	< 0.01	(0.81, 1.338)
ContrastDegree_High	1.41	0.15	< 0.01	(1.127, 1.697)

Eventually, after eliminating the non-significant characteristic elements through the stepwise regression method, the formulas of the GEE logistic regression equations for each perception are expressed as follows:

$$\begin{aligned}\text{Logit}(P(\text{Beauty})) = &0.81 + 0.09 \cdot \text{DT\_HP} + 0.46 \cdot \text{NE} - 8.45 \cdot \text{SR} - 6.13 \cdot \text{AO} \\ &+ 27.67 \cdot \text{WR} + 0.44 \cdot \text{DO\_M}\end{aligned} \tag{3.2}$$

Where the variables are defined as follows:

- **DT_HP**: DTHerb Plants
- **NE**: Number Of Elements
- **SR**: Sky Ratio
- **AO**: Artificial Objects
- **WR**: Water Ratio
- **DO_M**: Degree Of Openness Medium

$$\begin{aligned}\text{Logit}(P(\text{Comfort})) = &-2.46 + 0.38 \cdot \text{NE} + 7.81 \cdot \text{CC} - 4.14 \cdot \text{RR} \\ &+ 20.16 \cdot \text{WR} - 0.39 \cdot \text{PS\_L}\end{aligned} \tag{3.3}$$

Where the variables are defined as follows:

- **NE**: Number Of Elements
- **CC**: Crown Coverage
- **RR**: Road Ratio

- **WR**: Water Ratio
- **PS_L**: Planting Style Linear

$$\begin{aligned}\text{Logit}(P(\text{Color})) = & -2.52 - 0.17 \cdot \text{RC\_G} + 0.11 \cdot \text{NM} + 16.11 \cdot \text{WR} + 6.74 \cdot \text{FR} \\ & + 1.16 \cdot \text{CD\_H}\end{aligned} \tag{3.4}$$

Where the variables are defined as follows:

- **RC_G**: RC Grass
- **NM**: Number Of Materials
- **WR**: Water Ratio
- **FR**: Flower Ratio
- **CD_H**: Contrast Degree High

$$\begin{aligned}\text{Logit}(P(\text{Complexity})) = & -3.76 + 0.21 \cdot \text{RC\_HP} + 0.21 \cdot \text{SS} + 0.23 \cdot \text{NM} \\ & - 1.95 \cdot \text{RR} + 11.85 \cdot \text{WR} + 0.37 \cdot \text{PS\_G}\end{aligned} \tag{3.5}$$

Where the variables are defined as follows:

- **RC_HP**: RCHerb Plants
- **SS**: ShrubSpecies
- **NM**: Number Of Materials
- **RR**: Road Ratio
- **WR**: Water Ratio
- **PS_G**: Planting Style Group

$$\begin{aligned}\text{Logit}(P(\text{Liveliness})) = & -2.02 + 0.14 \cdot \text{DT\_HP} - 0.21 \cdot \text{SS} + 0.21 \cdot \text{NM} \\ & - 0.28 \cdot \text{STC} + 37.82 \cdot \text{WR} - 1.25 \cdot \text{DO\_H}\end{aligned} \tag{3.6}$$

Where the variables are defined as follows:

- **DT_HP**: DTHerb Plants
- **SS**: ShrubSpecies
- **NM**: Number Of Materials
- **STC**: Space Type Categories
- **WR**: Water Ratio
- **DO_H**: Degree Of Openness High

$$\text{Logit}(P(\text{Greenness})) = 2.66 - 0.03 \cdot \text{DT\_S} - 0.22 \cdot \text{RC\_AO} + 0.17 \cdot \text{SS} - 6.11 \cdot \text{RR} + 7.39 \cdot \text{WR} - 4.12 \cdot \text{HR} + 0.39 \cdot \text{DO\_L} + 1.24 \cdot \text{PS\_L} \tag{3.7}$$

Where the variables are defined as follows:

- **DT_S**: DT Shrub
- **RC_AO**: RCArtificial Objects
- **SS**: ShrubSpecies
- **RR**: Road Ratio
- **WR**: Water Ratio
- **HR**: Herb Ratio
- **DO_L**: Degree Of Openness Low
- **PS_I**: Planting Style Isolated

$$\text{Logit}(P(\text{Safety})) = -2.49 - 0.05 \cdot \text{DT\_T} + 0.66 \cdot \text{STC} + 1.07 \cdot \text{DO\_H} + 1.41 \cdot \text{CD\_H} \tag{3.8}$$

Where the variables are defined as follows:

- **DT_T**: DTTrees
- **STC**: Space Type Categories
- **DO_H**: Degree Of Openness High
- **CD_H**: Contrast Degree High

Through correlation and GEE logistic regression analyses, we excluded insignificant indicators and identified those that influenced human perception. Combination of three dimensions provided comprehensive visual assessment results. As shown in Table 3.11, eye-tracking indicators related to herb plants (DTHerbPlants and RCHerbPlants) showed the most extensive positive correlations, affecting the perceptions of beauty, complexity, and liveliness. Among the image segmentation indicators, WaterRatio showed the most extensive positive correlation, affecting the perceptions of beauty, comfort, color, complexity, liveliness, and greenness. NumberOfMaterials exhibited the most extensive positive correlations with the spatial feature indicators, affecting the perceptions of color, complexity, and liveliness. These findings emphasize the correlations between multidimensional visual indicators and human perceptions.

Table 3.11: Summary of key indicators and their correlations with human perception

Perception	Eye-tracking indicators	Image segmentation indicators	Spatial feature indicators
Beauty	DTHerbPlants (+)	WaterRatio (+), SkyRatio (–), and ArtificialObjects (–)	NumberOFElements (+), and DegreeOfOpenness_Medium (+)
Comfort	None	WaterRatio (+), RoadRatio (–), and CrownCoverage (+)	NumberOfElements (+), and PlantingStyle_Linear (–)
Color	RCGrass (–)	WaterRatio (+), and FlowerRatio (+)	NumberOfMaterials (+) and ContrastDegree_High (+)
Complexity	RCHerbPlants (+)	WaterRatio (+), and RoadRatio (–)	ShrubSpecies (+), NumberOfMaterials (+), and PlantingStyle_Group(+)
Liveliness	DTHerbPlants (+)	WaterRatio (+)	ShrubSpecies (–), NumberOfMaterials (+), SpaceTypeCategories (–), and DegreeOfOpenness_High (–)
Greenness	DTShrubs (–), and RCArtificialObjects (–)	WaterRatio (+), RoadRatio (–), and HerbRatio (–)	ShrubSpecies (+), DegreeOfOpenness_Low (+), and PlantingStyle_Isolated (+)
Safety	DTTrees (–)	None	SpaceTypeCategories (+), DegreeOfOpenness_High (+), and ContrastDegree_High (+)

Note: (+) represents positive correlation; (-) represents negative correlation.

3.3.3 Enhancing classification models using multidimensional visual indicators

Our classification models incorporating multidimensional visual indicators exhibited good performance in assessing the LVQ of urban parks. Our models exhibited robust performance in distinguishing between positive and negative perceptions of

Table 3.12: Comparison of model performance metrics (QIC and AUC).

Model	Multidimensional visual indicators		Spatial feature indicators		QIC Difference	AUC Difference
	QIC	AUC	QIC	AUC		
Beauty	1871.82	82%	2003.99	78%	132.17	4.0%
Comfort	2158.92	74%	2301.30	69%	142.38	5.0%
Color	2117.28	74%	2182.30	73%	65.02	1.0%
Complexity	2147.22	73%	2229.45	71%	82.23	2.0%
Liveliness	1864.32	81%	2015.63	78%	151.31	3.0%
Greenness	2160.98	74%	2332.99	67%	172.01	7.0%
Safety	2076.22	78%	2200.54	75%	124.32	3.0%

Note: QIC Difference = QIC (spatial feature indicators) - QIC (multidimensional visual indicators).
AUC Difference = AUC (multidimensional visual indicators) - AUC (spatial feature indicators).

urban park attributes by integrating eye-tracking, image segmentation, and spatial feature indicators. As shown in Table 3.12, we evaluated the effectiveness of the models using AUC and QIC metrics, which showed their ability to distinguish between perceptions and deliver reliable classification outcomes.

The AUC scores reflected the classification performance of our models in distinguishing between positive and negative perceptions of urban parks. Compared to models solely relying on spatial feature indicators, our models involving multidimensional visual indicators exhibited better performance, with notable improvements across all attributes, with an increase of 4% in beauty, 5% in comfort, 1% in color, 2% in complexity, 3% in liveliness, 7% in greenness, and 3% in safety. Although the degree of improvement varied, the overall enhancement highlights the advantages of incorporating multidimensional visual indicators into traditional models, particularly since models based solely on spatial feature indicators demonstrated higher QIC scores, indicating weaker model fit. In contrast, models incorporating multidimensional visual indicators demonstrate superior performance, emphasizing the significant benefit of integrating eye-tracking, image segmentation, and spatial feature indicators in enhancing the model accuracy and goodness-of-fit.

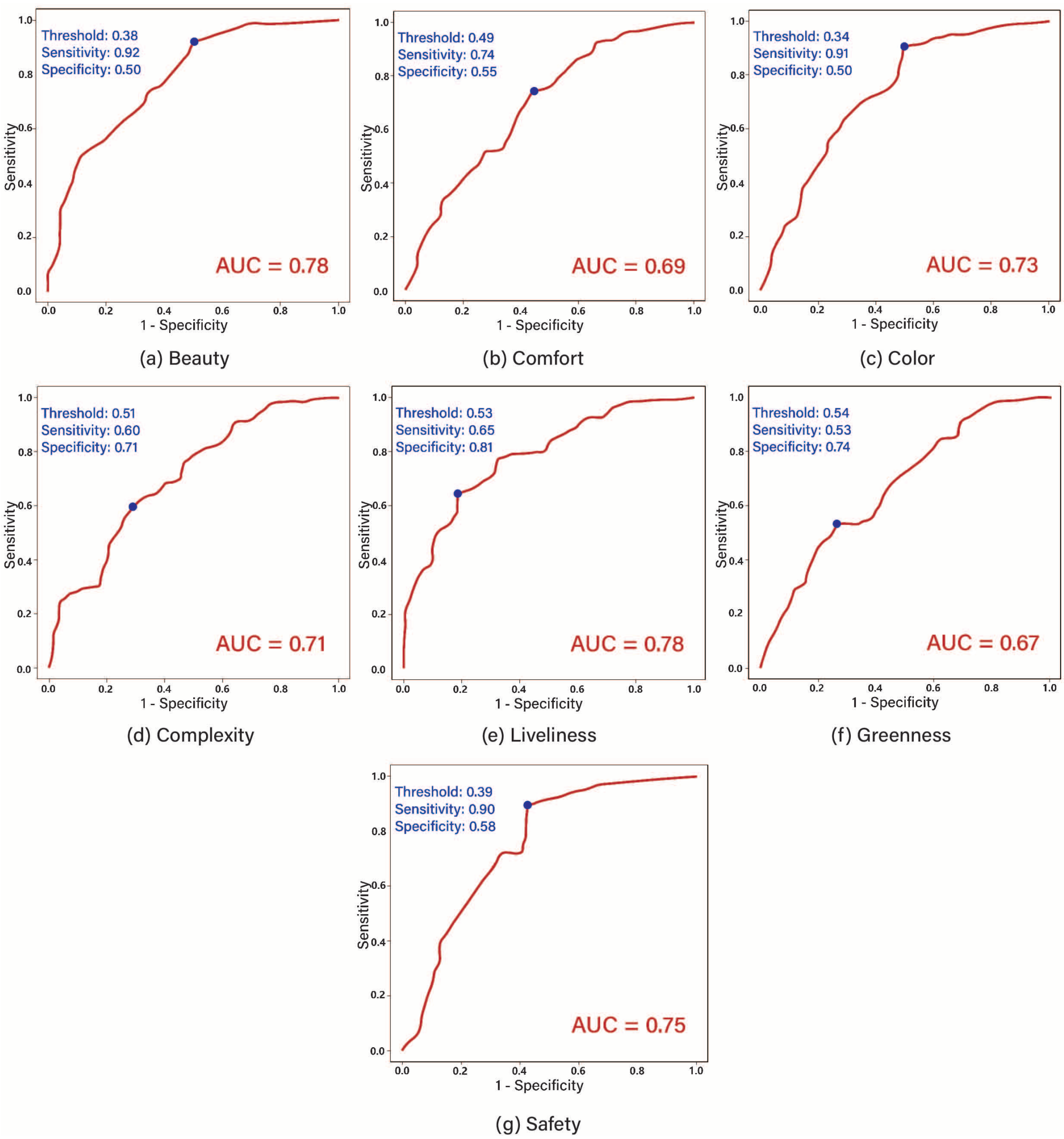


Figure 3.10: ROC curves derived from GEE logistic regression models using spatial feature indicators to assess seven human perceptions

3.4 Discussion

3.4.1 The impact of multidimensional visual indicators on human perception

(1) Comprehensive impact

In this study, eye-tracking, image segmentation, and spatial feature indicators each contribute to a predictive indicator that has the broadest impact on the human perceptual assessment of urban park across seven perceptual models. Specifically, these indicators were HerbPlants (DTHerbPlants and RCHerbPlants), WaterRatio, and NumberOfMaterials. Specific eye-tracking indicators related to herb plants, namely DTHerbPlants and RCHerbPlants, significantly influenced multiple perceptual models. The DTHerbPlants is an indicator that significantly affects multiple perceptual models. In models assessing beauty and liveliness, the extended dwell time on herb plants indicates an enhancement of the landscape's appeal and diversity through rich visual elements such as a variety of flower colors and species richness [88, 144]. A longer dwell time reflects the visual attractiveness of herb plants compared with ordinary green ornamental plants, providing more visual stimulation and aesthetic value to the landscape [88]. The positive correlation of RCHerbPlants with complexity suggests that the visual intricacy of herb plants, despite their limited area and uniformity in some settings, can significantly engage observers, contributing to a more complex visual experience [145]. WaterRatio is an essential indicator for assessing the LVQ of urban parks, correlating positively with various perceptions, including beauty, comfort, complexity, liveliness and greenness. High water ratio significantly enhances the beauty, comfort, and liveliness of urban parks [99, 146, 147]. Water-associated colors, such as blue, promote relaxation and pleasure, thereby enhancing color perception [148]. Eye-tracking data further support these findings, showing that areas with a higher proportion of water retain visitors' gazes significantly longer, indicating that these areas are more effective in attracting and maintaining human interest. The reflective properties of water surfaces play a key role in the positive correlation between WaterRatio and perceptions of complexity and greenness. Reflections of vegetation and structures add visual stimuli, enhancing scene complexity, while reflected greenery amplifies perceived green coverage, creating a synergistic effect that strengthens greenness perception [56]. NumberOfMaterials is positively correlated with perceptions of color, complexity, and liveliness, reflecting the influence of material diversity in uniquely designed, color-rich facilities and varied plant arrangements that enhance these attributes [132, 149].

We found that HerbPlants, WaterRatio, and NumberOfMaterials have significant impacts on multiple perceptual dimensions, reflecting the multidimensional integration of human perception [22, 127, 150]. HerbPlants significantly enhances perceptions of beauty and liveliness through its visual appeal and diversity, while simultaneously contributing to complexity due to the intricate details of herb plants [88, 149]. Similarly, WaterRatio not only promotes beauty and comfort through its aesthetic and restorative qualities but also enhances perceptions of color diversity due to its association with blue tones, while its reflective properties further enhance perceptions of complexity and greenness by mirroring vegetation, enriching the perceptual experience [147,148]. The diversity of materials represented by NumberOfMaterials enriches color and complexity while also increasing liveliness by offering varied visual experiences [151]. Due to the complex and comprehensive effects of these spatial features on visual appeal and psychological restoration, they often simultaneously influence different perceptual dimensions [107, 148]. This multidimensional influence demonstrates the interrelationships within environmental perception and provides a more holistic perspective for the overall assessment of urban parks [22,114,148,152]. The strong classification performance of the perceptual models further indicates that these potential overlaps do not undermine the validity of the findings; rather, they emphasize the important role these indicators play in the comprehensive evaluation of environmental perception.

(2) The impact of eye-tracking indicators

eye-tracking provides an insightful perspective on the ways in which users visually interact with urban park landscape elements. This technology reveals key indicators that influence various perceptual models, offering direct insights into user engagement and preference patterns. RCArtificialObjects negatively correlated with the perception of greenness. Artificial objects such as street lamps, noticeboards, and trash bins, characterized by their stark contrast with natural vegetation, have attracted significant attention [85, 153]. This attentional shift towards artificial objects leads to a diminished focus on vegetation, thereby negatively affecting the perceived greenness of the environment [154,155]. DTTrees negatively correlated with the perception of safety. This can be explained by prospect-refuge theory, as trees may act as visual obstructions that reduce openness, heightening vigilance and lowering perceived safety [127, 156]. The negative correlation between RCGrass and color perception may reflect the dominance of large grassland areas in the visual field. With their extensive coverage and uniform color, grasslands often attract repeated visual attention, limiting the exploration of more colorful elements and consequently reducing the perception of color diversity in the urban park. DTShrubs negatively correlated with greenness perception. By comparing spaces with similar green ratios, shrub ratios, and dwell time to shrubs, it was found that greenness perception was higher in spaces with greater shrub species diversity. This suggests that the negative correlation of DTShrubs may indirectly reflect the suppressive effect of low shrub species diversity on greenness perception.

In this study, eye-tracking data not only improved the accuracy of our classification models but also provided profound insights on the relationships revealed by image segmentation and spatial feature indicators. We found a negative correlation between HerbRatio and greenness perception. Despite their visual appeal and colorful flowering, herb plants negatively affect the overall perception of greenness as they draw attention away from green foliage, reducing the perceived greenness in areas with high concentrations of these plants [88]. Typically, increased RoadRatio reduces the perceptions of comfort, complexity, and greenness due to reduced vegetation [56, 157]. Eye-tracking data also supported this finding, showing that, in areas with a higher RoadRatio, human visual attention to green vegetation decreased, further reducing perceptions of these attributes. The diversity of shrub species correlated positively with perceptions of complexity and greenness, while showing a negative correlation with liveliness. Eye-tracking data revealed that areas with abundant shrubs attracted frequent and prolonged visual attention, enriching the scene's visual complexity. The diversity of shrub species enhances the perception of greenness by increasing the richness and variety of vegetation coverage [130]. The negative association with liveliness may stem from dense shrub arrangements, which not only obstruct open views but also limit the visibility of other landscape elements within space. Isolated planting positively influenced the perceptions of greenness. Although the planting style has been associated with perceptions in similar studies, its impact is generally not significant. To understand this relationship, we reviewed the study area, which included four scenes featuring trees with isolated planting styles. Examination of the eye-tracking gaze trajectory plots from these four scenes (Figure 3.11) revealed that isolated planting attracted the most attention, improving the perception of greenness.

(3) Other indicators Building on our multidimensional visual indicator approach, this section delves into the roles of other image segmentation and spatial feature indicators that shape urban park perceptions. ArtificialObjects negatively impact the perception of beauty, with artificial structures typically detracting from aesthetic quality owing to their stark contrast to natural elements [85]. Moreover, SkyRatio correlates negatively with beauty, which parallels the results of the Sky View Factor analysis at the street level [158]. Thus, we can show that SkyRatio's impact on perception extends beyond urban street landscapes and applies to urban parks in VR. Transitioning from factors that detract from the beauty of green spaces, several indicators significantly enhance the experience of green spaces. An increased CrownCoverage enhances comfort by providing extensive coverage [56]. FlowerRatio enhances color perception by increasing color diversity and adding visual appeal to the greenspace environment [88]. NumberOfElements is positively

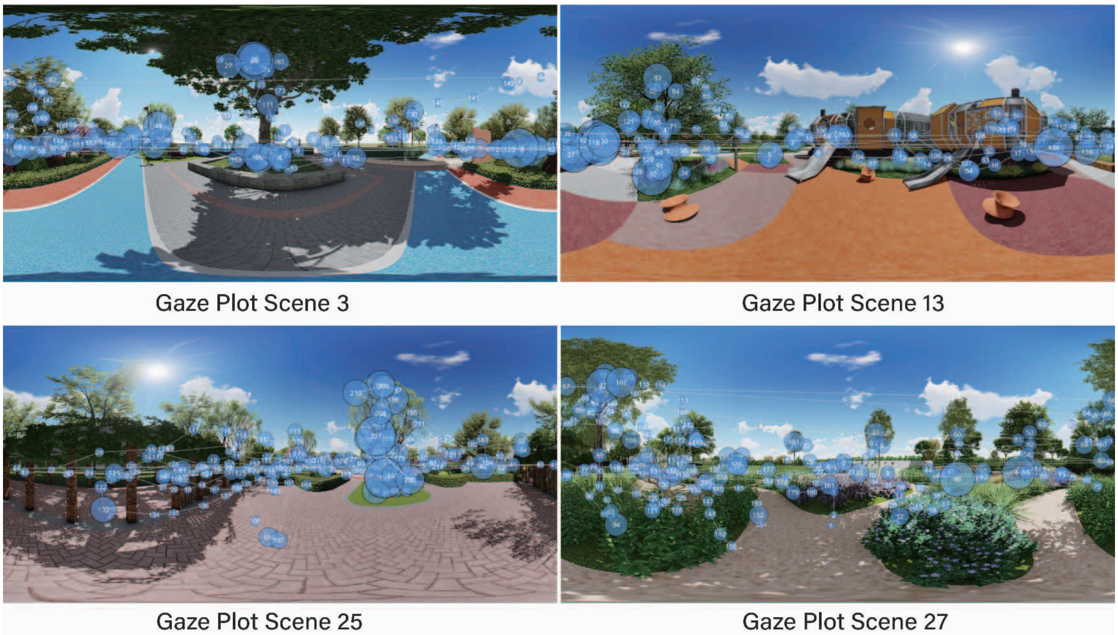


Figure 3.11: Gaze plot of an isolated planting style scene. The circles displayed represent the user's points of gaze, and the size of the circles is proportional to the duration of the gaze

correlated with perceptions of beauty and comfort. The diversity of elements is positively associated with perceptions of beauty and psychological comfort by increasing visual complexity and creating more visually appealing scenes [151,159]. SpaceTypeCategories positively correlated with safety. A variety of visible space types enhances safety perceptions by improving visibility and reducing potential hiding spots through unobstructed views [156]. Fragmented space types, which disrupt spatial continuity, may account for the negative correlation with liveliness [160,161]. ContrastDegree significantly influenced perceptions of color, and safety. High contrast levels enhance color perception and show a positive correlation with safety, likely due to their frequent use in activity areas, where brightly colored equipment improves visibility and reduces uncertainty [22,162]. A medium level of openness positively correlates with the perception of beauty [122,163,164], this study further specifies that the degree of openness between 20–80% is mainly associated with increased beauty perception. In contrast, high degrees of openness negatively affect complexity and liveliness perceptions, as our analysis of panoramic photos in highly open areas showed that elements within a 15-m radius tend to be uniformly sparse, leading to a simpler visual landscape. Low degrees of openness were positively correlated with greenness perception, likely because green spaces with lower openness are often enclosed by arranged vegetation, enhancing the perception of greenery. In contrast, high degrees of openness enhance safety perception by providing clear sightlines and minimizing potential hiding spots, aligning with the principles of prospect-refuge theory [156]. PlantingStyle_Linear was negatively correlated with perceptions of comfort, likely due to its uniform and rigid structure, which lacks the visual richness necessary to promote relaxation and mental ease in urban parks [121]. PlantingStyle_Group positively correlated with perceptions of complexity, as grouped planting arrangements create varied and layered vegetation patterns, enhancing the perception of complexity.

3.4.2 The performance of perception model integrating multidimensional visual indicators

Assessment of LVQ in urban parks is crucial to avoid resource wastage and prevent negative impacts due to unmet human expectations. This study introduced an integrated method that combines VR technology, eye-tracking, and image segmentation to effectively assess the perceived LVQ of urban parks. Compared to methods that rely on two-dimensional rendering, immersive VR technology provides a more realistic sensory experience by simulating environments that are yet to be constructed [77], thus overcoming the limitations of traditional techniques and enhancing the visualization and interactivity of designs [116]. This study identified and recorded zones of maximum visual attention using eye-tracking technology, offering empirical data on focal points within urban park environments [165–167]. Image segmentation technology divides visual content into distinct parts, such as the green ratio, water ratio, and artificial objects, facilitating detailed analysis of the mechanisms by which these segments contribute to the overall perceptual quality [56, 168]. Combining spatial feature indicators such as openness and planting style with eye-tracking and image segmentation indicators offers a more comprehensive evaluation perspective. This multidimensional integration enabled the model to comprehensively capture the diverse features of greenspace environments. Multidimensional visual indicators improved the model's ability to differentiate between positive and negative perceptions of urban park attributes by 1–7%. Furthermore, the lower QIC scores of the multidimensional visual classification model indicate a better fit compared to models relying solely on spatial feature indicators. These findings emphasize the advantages of incorporating multidimensional visual indicators to enhance the performance and goodness-of-fit of classification models.

3.5 Summary

This study demonstrated the efficacy of VR-based multidimensional visual indicators in enhancing LVQ assessment of urban parks. Using a VR-based multifaceted approach, we developed a set of multidimensional visual indicators to understand the impact of LVQ on human perception of urban parks. The integrated model demonstrated a better fit and distinguished more effectively between positive and negative perceptions compared to models using only spatial feature indicators. Therefore, our integrated model incorporating various multidimensional visual indicators accurately classifies human perceptions of urban park LVQ. Our approach allows for pre-assessment of LVQ before urban park construction, enabling planners to make informed design adjustments early in the process.

This study makes important contributions to the assessment of LVQ in urban park. First, this study analyzed the correlations between multidimensional visual indicators (eye-tracking, image segmentation, and spatial feature indicators) and human perceptions, highlighting the ways in which these elements influence the human perceptions of urban park landscapes. Herb plants, water ratio, and number of materials were the most positively correlated indicators (eye-tracking, image segmentation, and spatial feature indicators, respectively) influencing human perception. Second, this study explored the correlations between human perceptions and urban park landscape environments using eye-tracking data. Isolated planting styles, which drew the most attention, positively impacted the greenness perception. Perceptions of beauty, complexity, and liveliness were positively correlated with eye-tracking data from herb plants, whereas perceptions of greenness were negatively correlated with the HerbRatio. SkyRatio was negatively correlated with beauty, consistent with the street-level analysis results. Moderate degree of openness (20–80%) positively correlated with beauty, establishing a range for openness. However, high openness led to a monotonous visual landscape, as elements within a 15-meter radius tend to be uniformly sparse, thereby reducing the perceived liveliness of urban parks but enhancing the perception of safety. Shrub species diversity enhances perceptions of greenness and complexity by enriching vegetation richness and visual complexity. In contrast, low shrub species diversity, as reflected in dwell time to shrubs, suppresses greenness perception. Additionally, dense shrubs can obstruct open views and limit the visibility of other landscape elements, which may reduce perceptions of liveliness. Based on these findings, we propose several design guidelines for urban park development that can help urban planners and landscape designers enhance LVQ while meeting user expectations: 1) Incorporate a variety of herb plants to create a visually appealing and dynamic landscape, positively impacting perceptions of beauty, complexity, and liveliness. 2) Maintain a visible water ratio within the space to enrich human perceptions, achieved through integrating fountains or other water features. 3) Use moderate openness levels (20–80%) to balance beauty perception, avoiding overly open designs that may lead to visual monotony. 4) Ensure visually engaging elements within a 15-meter radius to prevent sparse landscapes, as insufficient density can reduce perceived complexity and liveliness. 5) Designing with diverse shrub species while avoiding dense single-species planting can enhance perceptions of greenness and complexity while maintaining a balance in liveliness perception. Overall, our findings and the proposed assessment approach can assist landscape designers and urban planners in enhancing the LVQ of urban parks. Our approach can help to meet public expectations before urban park construction, prevent resource wastage, and support sustainable urban development. Future studies should evaluate the efficiency of our assessment method in other space designs.

Chapter 4

Emotional dimensions of landscape visual quality

4.1 Introduction

As urbanization accelerates, the design and evaluation of urban parks have become increasingly important for promoting emotional well-being and enhancing urban life quality [25, 26]. Landscape visual quality (LVQ)—defined as the interaction between landscape features and human perception—has emerged as a key indicator of successful park design [88,151,169]. Building on Study 1's investigation into the perceptual dimensions of LVQ (e.g., beauty, comfort, color, complexity, liveliness, greenness, and safety), this chapter shifts focus to the emotional dimension. It adopts a multimodal approach integrating physiological signals (e.g., electrodermal activity, PR), eye-tracking data, and self-reported emotional ratings via the Self-Assessment Manikin (SAM), offering a comprehensive perspective on how landscape elements influence emotional responses.

Emotional responses are essential for understanding how specific landscape elements shape user experience. While Study 1 identified positive and negative spaces based on perceptual qualities, Study 2 seeks to bridge perception and emotion by embedding LVQ evaluation within an emotional framework. This study employs immersive VR environments—constructed via SketchUp modeling and Lumion rendering—to simulate urban park settings under controlled experimental conditions. Landscape elements were isolated and manipulated to investigate their impact on user experience. Emotional data were captured through physiological measurements (e.g., skin conductance, PR) and subjective self-assessments (SAM), while visual behavior was recorded using eye-tracking technology to explore attentional patterns. These methods provide an integrative understanding of how emotional states and visual engagement interact with LVQ, generating practical insights for emotionally supportive park design. Specifically, this study addresses the following research questions:

- How do landscape element proportions relate to visual behavior and emotional responses?

- How does visual behavior toward different landscape element types influence emotional responses?
- How does visual behavior explain the relationship between landscape elements and emotional responses?

4.2 Method

4.2.1 Data collection overview

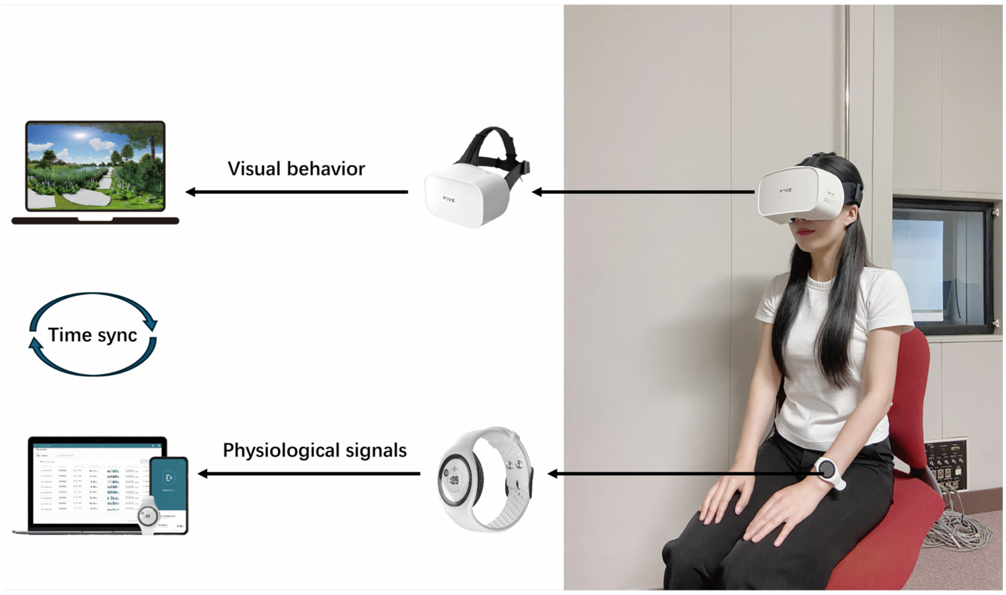


Figure 4.1: Experimental device wear and data synchronization process.

This study builds upon data collected in the same experiment as Study 1 but focuses on a different portion of the dataset. While Study 1 emphasized dwell time and revisit count from the eye-tracking data to assess LVQ, Study 2 broadens the analysis by incorporating all eye-tracking indicators, including time to first fixation (TTFF), dwell time (DT), fixation ratio (FR), revisit count (RC), first fixation duration (FFD), and average fixation duration (AFD). To explore the emotional dimensions of LVQ, this study also integrates physiological measurements and the SAM scale to examine how landscape elements influence both emotional responses and visual behavior. Data collection followed the same protocol outlined in Study 1 (refer to section 3.2), using the NeU-VR device and integrated eye-tracking technology. Physiological measurements were captured using the EmbracePlus smartwatch, and emotional responses were recorded using

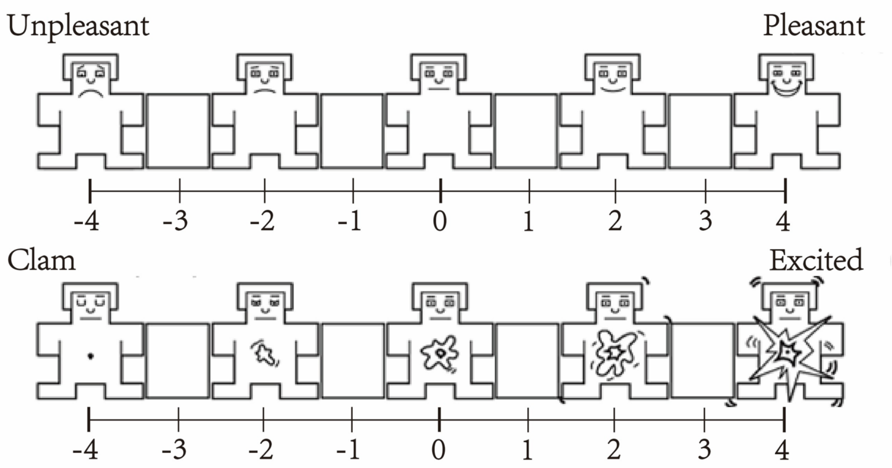


Figure 4.2: Self-Assessment Manikin.

the SAM sacle. Together, these tools provided a multidimensional framework for quantifying the emotional dimensions of LVQ in controlled yet immersive virtual environments.

4.2.2 Physiological measurements

This device continuously recorded EDA and PR, synchronized via Bluetooth to the Empatica health monitoring platform for real-time data processing and cloud-based storage (Figure 4.1). EDA, an established indicator of sympathetic nervous system activation, is extensively used as a physiological marker of emotional arousal [170]. PR, modulated by both sympathetic and parasympathetic activity, serves as a physiological indicator of responses to emotional stimuli [171].

4.2.3 Psychological measurements

Psychological emotional responses were assessed via the SAM scale [27], which evaluates valence, arousal, and dominance. Following previous studies [172], only valence (unpleasant to pleasant) and arousal (calm to excited) were analyzed, since restricted participant movement minimized dominance-related effects. Emotional responses were rated on a nine-point scale (Figure 4.2). This concise tool is well-suited for capturing immediate emotional reactions within virtual park environments, providing valuable insights into the emotional dimensions of LVQ.

4.2.4 Visual behavior indexes

Eye-tracking technology was employed to analyze gaze behavior and identify how landscape elements influence emotional arousal. The data provided an objective and quantifiable means of understanding visual behavior within virtual environments, directly contributing to the evaluation of LVQ. This study analyzed six key types of eye-tracking data to capture participants' visual behavior comprehensively (Table 4.1). Real-time data visualization tools, including heatmaps and gaze trajectory diagrams, were used to analyze participants' attention allocation. This analysis enabled the identification of visual behaviors that are closely tied to emotional responses and LVQ. The detailed definitions and explanations of all indicators are provided in Appendix C.

Table 4.1: Eye-tracking indexes for different landscape elements.

Abbreviation	Full name	Definition and explanation
TTFF	Time To First Fixation	The time taken from the onset of a stimulus until the first fixation on a specific Area of Interest (AOI); reflects the priority of visual elements.
FFD	First Fixation Duration	The duration of the initial gaze at this AOI; reflects visual initial processing.
DT	Dwell Time	The total time the user's gaze stayed within the AOI; reflects the user's interest and engagement.
RC	Revisit Count	The number of times the user's gaze entered the AOI; reflect the element's importance or attractiveness.
FR	Fixation Ratio	The ratio of the amount of time the user spends in a particular AOI to the total amount of time spent in all AOI; reflects the relative importance or complexity.
AFD	Average Fixation Duration	Mean of fixation duration on each AOI; reflects the depth of cognitive processing.

4.2.5 Quantifying landscape elements

The proportions of seven landscape elements in 30 panoramic images were analyzed to explore their influence on emotional responses and LVQ. These elements included:

- Natural elements: Trees, shrubs, flowering trees, grass, herb plants, and water landscapes.
- Artificial objects: Roads, street lamps, benches, sculptures, game facilities, and buildings.

To extract and quantify landscape elements in panoramic images, this study utilized an interactive semi-automatic image annotation tool (ISAT) integrated with the segment-anything model [119]. Following segmentation (Figure 4.3), Python scripts were employed to process the annotated images, extract pixel distributions, and compute the proportional coverage of each landscape element.

4.2.6 Data analysis

Eye-tracking data were analyzed with FOVE Gaze Analyzer (FOVE) and PyCharm Community Edition 2023.2.1 (JetBrains s.r.o., Czech Republic). Raw data were processed into structured metrics by aggregating redundant instances of the same landscape element (e.g., Grass1 and Grass2 were merged into a single variable named Grass). The extracted eye-tracking metrics comprised TTFF, FFD, RC, DT, FR, and AFD. Physiological signals, recorded as time-series data, were extracted for each participant during the one-minute viewing of each panoramic image, synchronized using timestamps.

Shapiro-Wilk tests and histogram analyses confirmed that data from the SAM scale, physiological signals, eye-tracking metrics, and landscape element proportions did not follow normal distribution. Consequently, Spearman's rank correlation was used to assess associations among landscape element proportions, emotional responses, physiological signals, and visual behavior. The Kruskal-Wallis H test evaluated differences in eye-tracking metrics across landscape element types, while partial Spearman's rank correlation controlled confounding variables when analyzing relationships between visual behavior, emotional responses, and physiological signals. Composite emotional scores were derived from SAM scale data to rank scenes based on their extremity in emotional responses (most positive and most negative). Finally, eye-tracking heatmaps were generated to visualize key visual attention regions across different emotional conditions, identifying landscape elements associated with emotional responses.

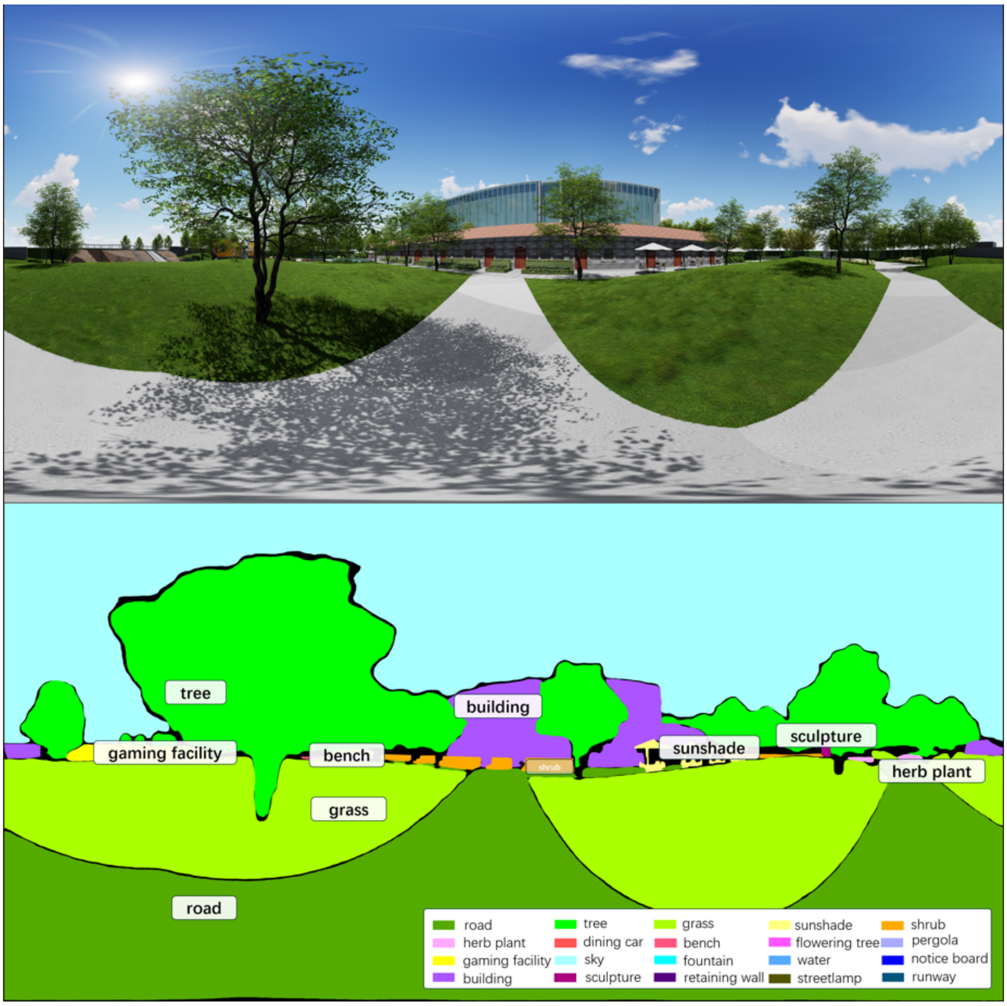


Figure 4.3: Panoramic pictures and semantic segmentation results.

4.3 Results

4.3.1 Effect of landscape element proportions on emotional responses and visual behavior

Correlation of landscape element proportions with emotional responses
(1) Psychological results

Table 4.2: Spearman correlation coefficients (ρ) between landscape element proportions and psychological changes.

Variable		Trees	Shrubs	Flower Trees	Grass	Herb Plants	Water Land-scape	Artificial Objects
Valence	r	0.099	-0.359	-0.044	0.165	0.574**	0.350	-0.169
	ρ	0.602	0.052	0.817	0.384	<0.01	0.058	0.372
Arousal	r	-0.111	-0.442*	-0.235	0.194	0.677**	0.347	-0.012
	ρ	0.561	<0.05	0.211	0.303	<0.01	0.060	0.950

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

The analysis of the correlation between landscape element proportions and emotional psychological changes, as shown in Table 4.2, reveals that herb plants have a significant positive correlation with both the valence and arousal components of emotions ($p < 0.01$). This indicates that the presence of herb plants in the landscape is associated with higher levels of positive emotions and increased arousal. Conversely, shrubs exhibit a negative correlation with arousal ($p < 0.05$), suggesting that higher proportions of shrubs might be linked to reduced emotional arousal.

(2) Physiological results

In terms of physiological changes, as detailed in Table 4.3, the results show that only Flower Trees have a notable correlation with physiological responses. Specifically, Flower Trees are significantly positively correlated with EDA ($r = 0.597$, $p < 0.01$), indicating increased sympathetic nervous system activity. Additionally, Flower Trees are significantly negatively correlated with PR ($r = -0.683$, $p < 0.01$), suggesting a calming effect on PR. This highlights the unique impact of Flower Trees on physiological signals compared to other landscape elements.

Correlation of landscape element proportions with visual behavior

The analysis of correlations between landscape element proportions and eye-tracking indicators (Table 4.4) shows that, apart from FlowerTrees metrics showing

Table 4.3: Spearman correlation coefficients (ρ) between landscape element proportions and physiological changes.

Variable		Trees	Shrubs	Flower Trees	Grass	Herb Plants	Water Landscape	Artificial Objects
EDA	r	0.039	0.119	0.597**	-0.057	0.236	0.187	-0.107
	ρ	0.836	0.529	<0.01	0.765	0.210	0.323	0.574
PR	r	-0.160	-0.081	-0.683**	-0.174	-0.018	0.005	0.239
	ρ	0.399	0.669	<0.01	0.359	0.926	0.978	0.203

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

no correlation with eye-tracking indicators and no correlation between Trees and TTFF, other landscape element proportions are positively correlated with TTFF, FFD, RC, DT, FR, and AFD. Taking HerbPlants as an example, the Pearson r values for eye tracking indicators are high (TTFF r=0.883, FFD r=0.947, RC r=0.941, DT r=0.936, FR r=0.938, AFD r=0.944). This indicates that the higher the proportion of landscape elements, the quicker people gaze at them, the longer the initial fixation duration, the more frequent the revisits, the longer the total dwell time, the higher the fixation ratio, and the longer the average fixation duration.

4.3.2 Effect of landscape element types on emotional responses and visual behavior

Correlation between visual behavior of different elements and emotional responses

(1) Time to first fixation and emotional responses:

The analysis in Table 4.5 shows that TTFF for herb plants is significantly and positively correlated with valence and arousal, indicating that the earlier people focus on herb plants, the more pleasant and excited they will be. Water landscapes were positively correlated with valence, indicating that the earlier people focus on water landscapes, the more pleasant they would be. Grass was significantly positively correlated with arousal, indicating that the earlier people focused on grass, the more excited they would be. On the other hand, TTFF for shrubs was significantly negatively correlated with valence and arousal, indicating that the earlier people focused on shrubs, the more likely they were to feel unpleasant and calm.

Table 4.4: Spearman correlation coefficients (ρ) between landscape element proportions and visual behavior.

Elements		TTFF	FFD	RC	DT	FR	AFD
Trees	r	0.180	0.565**	0.645**	0.489**	0.483**	0.578**
	ρ	0.341	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Shrubs	r	0.646**	0.880**	0.859**	0.868**	0.861**	0.883**
	ρ	< 0.01	< 0.01	< 0.01	< 0.01	<0.01	< 0.01
FlowerTrees	r	0.209	0.185	0.219	0.208	0.219	0.195
	ρ	0.268	0.328	0.245	0.270	0.245	0.302
Grass	r	0.739**	0.888**	0.881**	0.899**	0.886**	0.877**
	ρ	< 0.01	< 0.01	< 0.01	< 0.01	<0.01	< 0.01
HerbPlants	r	0.883**	0.947**	0.941**	0.936**	0.938**	0.944**
	ρ	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
WaterLandscape	r	0.935**	0.942**	0.939**	0.941**	0.941**	0.942**
	ρ	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
ArtificialObjects	r	0.594**	0.750**	0.705**	0.762**	0.766**	0.735**
	ρ	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

Table 4.5: Correlation coefficients between TTFF and emotion of landscape elements.

	Elements	Valence	Arousal	EDA	Pulse_Rate
TTFF	Trees	-0.030	-0.082	-0.276	0.117
	Shrubs	-0.499**	-0.469**	-0.020	0.121
	FlowerTrees	-0.219	-0.344	-0.311	0.115
	Grass	0.261	0.475**	0.019	-0.007
	HerbPlants	0.598**	0.704**	0.120	0.099
	WaterLandscape	0.420*	0.338	0.247	-0.079
	ArtificialObjects	0.077	0.136	-0.327	0.355

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

Table 4.6: Correlation coefficients between FFD and emotion of landscape elements.

	Elements	Valence	Arousal	EDA	Pulse_Rate
FFD	Trees	-0.020	-0.209	-0.293	-0.017
	Shrubs	-0.500**	-0.513**	-0.002	0.064
	FlowerTrees	-0.190	-0.362*	-0.203	0.105
	Grass	0.150	0.311	0.004	-0.052
	HerbPlants	0.575**	0.666**	0.243	0.023
	WaterLandscape	0.429*	0.346	0.216	-0.059
	ArtificialObjects	-0.016	0.093	-0.103	0.130

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

(2) First fixation duration and emotional responses:

As shown in Table 4.6, the FFD on herb plants is significantly positively correlated with both valence and arousal, suggesting that the longer people initially fixate on herb plants, the more pleasant and excited they feel. The FFD for water landscapes is also positively correlated with valence, indicating that longer initial gazes on water landscapes are associated with increased pleasantness. In contrast, the FFD for shrubs is significantly negatively correlated with both valence and arousal, implying that prolonged first gazes on shrubs tend to be associated with feelings of unpleasantness and calmness. Additionally, Flower trees show a negative correlation with arousal, indicating that longer initial fixations on Flower Trees correspond to a calmer.

(3) Revisit count and emotional responses:

As shown in Table 4.7, the RC for herb plants is significantly positively correlated with both valence and arousal, indicating that the more frequently people revisit herb plants, the more pleasant and excited they feel. The RC for water landscapes is positively correlated with valence, suggesting that more frequent revisits to water landscapes are associated with increased feelings of pleasantness. On the other hand, the RC for shrubs is negatively correlated with both valence and arousal, indicating that the more often people revisit shrubs, the more unpleasant and calm they tend to feel.

(4) Dwell time and emotional responses:

As shown in Table 4.8, the DT for herb plants is significantly positively correlated with both valence and arousal, indicating that the longer people gaze at herb plants, the more pleasant and excited they feel. The DT for water landscapes is positively correlated with valence, suggesting that the longer the gaze on water landscapes, the more pleasant people feel. On the other hand, the DT for shrubs is significantly negatively correlated with both valence and arousal, indicating that the longer people gaze at shrubs, the more unpleasant and calm they tend to feel. Additionally, the DT for Flower Trees is negatively correlated with arousal,

Table 4.7: Correlation coefficients between RC and emotion of landscape elements.

	Elements	Valence	Arousal	EDA	Pulse_Rate
RC	Trees	-0.004	-0.237	-0.204	0.097
	Shrubs	-0.369*	-0.385*	0.103	0.019
	FlowerTrees	-0.150	-0.342	-0.104	0.041
	Grass	0.028	0.169	-0.006	-0.149
	HerbPlants	0.517**	0.600**	0.276	0.014
	WaterLandscape	0.429*	0.338	0.194	-0.08
	ArtificialObjects	-0.061	0.112	0.147	-0.028

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

Table 4.8: Correlation coefficients between DT and emotion of landscape elements.

	Elements	Valence	Arousal	EDA	Pulse_Rate
DT	Trees	-0.118	-0.311	-0.316	0.107
	Shrubs	-0.426*	-0.404*	0.011	0.099
	FlowerTrees	-0.190	-0.365*	-0.151	0.081
	Grass	0.157	0.293	0.004	-0.133
	HerbPlants	0.542**	0.622**	0.272	0.016
	WaterLandscape	0.436*	0.347	0.198	-0.069
	ArtificialObjects	-0.027	0.117	0.023	0.010

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

suggesting that longer gazes on Flower Trees are associated with a calmer.

(5) Fixation rate and emotional responses:

As shown in Table 4.9, the FR for herb plants is significantly positively correlated with both valence and arousal, indicating that the higher the fixation rate on herb plants, the more pleasant and excited people feel. The FR for water landscapes is positively correlated with valence, suggesting that higher fixation rates on water landscapes are associated with increased feelings of pleasantness. On the other hand, the FR for trees is significantly negatively correlated with both valence and arousal, indicating that higher fixation rates on trees tend to be associated with feelings of unpleasantness and calmness. Additionally, the FR for shrubs and Flower Trees is negatively correlated with arousal, suggesting that higher fixation rates on these elements correspond to a calmer.

(6) Average fixation duration and emotional responses:

As shown in Table 4.10, the AFD for herb plants is significantly positively correlated with both valence and arousal, indicating that the longer the average fixation duration on herb plants, the more pleasant and excited people feel. The AFD for water landscapes is positively correlated with valence, suggesting that

Table 4.9: Correlation coefficients between FR and emotion of landscape elements.

	Elements	Valence	Arousal	EDA	Pulse_Rate
FR	Trees	-0.114*	-0.308*	-0.344	0.109
	Shrubs	-0.444	-0.422*	0.01	0.092
	FlowerTrees	-0.191	-0.371*	-0.145	0.073
	Grass	0.152	0.289	0.013	-0.116
	HerbPlants	0.541**	0.627**	0.258	0.031
	WaterLandscape	0.436*	0.347	0.198	-0.069
	ArtificialObjects	-0.013	0.124	0.003	0.024

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

Table 4.10: Correlation coefficients between AFD and emotion of landscape elements.

	Elements	Valence	Arousal	EDA	Pulse_Rate
AFD	Trees	-0.051	-0.245	-0.289	-0.031
	Shrubs	-0.489**	-0.511**	0.014	0.070
	FlowerTrees	-0.184	-0.372*	-0.184	0.093
	Grass	0.143	0.313	-0.016	-0.046
	HerbPlants	0.572**	0.655**	0.244	0.02
	WaterLandscape	0.432*	0.345	0.212	-0.068
	ArtificialObjects	0.039	0.111	-0.14	0.164

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

longer average fixation durations on water landscapes are associated with increased feelings of pleasantness. On the other hand, the AFD for shrubs is significantly negatively correlated with both valence and arousal, indicating that longer average fixation durations on shrubs tend to be associated with feelings of unpleasantness and calmness. Additionally, the AFD for Flower Trees is negatively correlated with arousal, suggesting that longer average fixation durations on Flower Trees correspond to a calmer.

In addition, eye-tracking behavior of landscape elements was not significantly correlated with EDA and PR.

(7) Summary of correlations between visual behavior and emotional responses by landscape type

Our analysis revealed distinct effects of landscape elements on emotional responses, as measured through eye movement metrics (TTFF, FFD, RC, DT, FR, AFD) and their correlation with valence, arousal, EDA, and PR. We found strong correlations between the visual behavior elicited by these elements and psychological responses, but these correlations varied significantly across different elements. In this study, we found that aside from the FR of shrubs, which

Table 4.11: Biased Spearman correlation analysis of control trees ratio, valence, arousal, EDA, PR and eye-tracking data.

Elements controlled	Emotion indicators	TTFF	FFD	DT	RC	FR	AFD
Trees	Valence	-0.049	-0.093	-0.192	-0.09	-0.186	-0.134
	Arousal	-0.064	-0.179	-0.296	-0.218	-0.292	-0.223
	EDA	-0.288	-0.382*	-0.385*	-0.301	-0.415*	-0.382*
	Pulse_Rate	0.150	0.090	0.214	0.264	0.216	0.076

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

showed no significant correlation with valence, all other eye-tracking behaviors induced by shrubs demonstrated a consistent negative correlation with both valence and arousal. Moreover, all eye-tracking behaviors induced by herb plants were positively correlated with both valence and arousal. Similarly, all eye-tracking behaviors induced by water landscapes showed a positive correlation with valence. For flowering trees, with the exception of TTFF and RC, the remaining metrics generally exhibited a negative correlation with arousal. Additionally, the TTFF for grasslands was positively correlated with arousal. However, these visual behaviors showed weak correlations with physiological responses such as EDA and PR.

Partial correlation analysis of different landscape elements

(1) Ratio of trees

The Table 4.11 results show that, when controlling for the tree ratio, the correlations between eye-tracking indicators and valence and arousal are weak and not statistically significant. However, certain eye-tracking indicators (such as FFD, DT, FR, and AFD) have a significant negative correlation with EDA. This suggests that longer initial fixation, longer attention duration, higher fixation rate, and longer average fixation time on trees may lead to a calmer physiological response. No significant correlations were found between PR and the eye-tracking indicators.

(2) Ratio of shrubs

The Table 4.12 results show that, when controlling for the shrub ratio, certain eye-tracking indicators (such as TTFF, FFD, and AFD) show a significant negative correlation with valence. This indicates that faster initial fixation on shrubs, longer initial fixation duration, and longer average fixation time may result in unpleasant feelings. The correlations between arousal, EDA, and PR with these eye-tracking indicators are weak and not statistically significant, suggesting that the impact of shrubs on these physiological and emotional indicators is limited or inconsistent.

(3) Ratio of flower trees

Table 4.12: Biased Spearman correlation analysis of control shrubs ratio, valence, arousal, EDA, PR and eye-tracking data.

Elements controlled	Emotion indicators	TTFF	FFD	DT	RC	FR	AFD
Shrubs	Valence	-0.376*	-0.416*	-0.248	-0.127	-0.285	-0.394*
	Arousal	-0.267	-0.292	-0.046	-0.012	-0.090	-0.286
	EDA	-0.128	-0.226	-0.188	0.000	-0.184	-0.196
	Pulse_Rate	0.228	0.287	0.342	0.175	0.320	0.303

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

Table 4.13: Biased spearman correlation analysis of control flower trees ratio, valence, arousal, EDA, PR and eye-tracking data.

Elements controlled	Emotion indicators	TTFF	FFD	DT	RC	FR	AFD
FlowerTrees	Valence	-0.213	-0.185	-0.185	-0.144	-0.186	-0.179
	Arousal	-0.318	-0.334	-0.332	-0.307	-0.337	-0.343
	EDA	-0.476**	-0.397*	-0.351	-0.3	-0.352	-0.382*
	Pulse_Rate	0.278	0.323	0.312	0.267	0.313	0.316

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

Table 4.14: Biased spearman correlation analysis of control grass ratio, valence, arousal, EDA, PR and eye-tracking data.

Elements controlled	Emotion indicators	TTFF	FFD	DT	RC	FR	AFD
Grass	Valence	0.210	0.007	0.020	-0.252	0.012	-0.004
	Arousal	0.502**	0.307	0.276	-0.005	0.258	0.302
	EDA	0.091	0.119	0.126	0.093	0.137	0.070
	Pulse_Rate	0.182	0.225	0.054	0.009	0.084	0.226

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

The Table 4.13 results show that, when controlling for the flower tree ratio, the impact of flower trees on valence and arousal is weak and not statistically significant. However, certain eye-tracking indicators (such as TTFF, FFD, and AFD) have a significant negative correlation with EDA. This suggests that faster initial fixation, longer initial fixation duration, and longer average fixation time on flower trees may lead to a calmer physiological state. The positive correlations between PR and the eye-tracking indicators are also not statistically significant, indicating that the impact of flower trees on PR is limited.

(4) Ratio of grass

The Table 4.14 results show that, when controlling for the grass ratio, the correlations between eye-tracking indicators and valence are weak and not statistically significant. There is a significant positive correlation between arousal and TTFF, indicating that the quicker people fixate on the grass, the more likely they are to feel excited. The correlations between EDA and PR with the eye-tracking indicators are weak, suggesting that the impact of grass on these physiological indicators is limited.

(5) Ratio of herb plants

The Table 4.15 results show that, when controlling for the herb plants ratio, the correlations between herb plants and valence, arousal, as well as physiological signals (EDA and PR) are weak and not statistically significant. This suggests that herb plants have a limited impact on these psychological and physiological indicators.

(6) Ratio of water landscapes

The Table 4.16 results show that, when controlling for the water landscapes ratio, the correlations between water landscapes and valence, arousal, as well as physiological signals (EDA and PR) are weak and not statistically significant. This suggests that water landscapes have a limited impact on these psychological and physiological indicators.

Table 4.15: Biased spearman correlation analysis of control herb plants ratio, valence, arousal, EDA, PR and eye-tracking data.

Elements controlled	Emotion indicators	TTFF	FFD	DT	RC	FR	AFD
HerbPlants	Valence	0.236	0.120	0.015	-0.084	0.010	0.110
	Arousal	0.309	0.106	-0.043	-0.147	-0.027	0.067
	EDA	-0.194	0.062	0.151	0.165	0.110	0.067
	Pulse_Rate	0.244	0.123	0.092	0.092	0.138	0.112

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

Table 4.16: Biased spearman correlation analysis of control water landscapes ratio, valence, arousal, EDA, PR and eye-tracking data.

Elements controlled	Emotion indicators	TTFF	FFD	DT	RC	FR	AFD
WaterLandscape	Valence	0.277	0.314	0.333	0.311	0.333	0.324
	Arousal	0.040	0.062	0.065	0.036	0.065	0.056
	EDA	0.207	0.120	0.068	0.053	0.068	0.108
	Pulse_Rate	-0.236	-0.188	-0.217	-0.248	-0.217	-0.218

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

Table 4.17: Biased spearman correlation analysis of control artificial objects ratio, valence, arousal, EDA, PR and eye-tracking data.

Elements controlled	Emotion indicators	TTFF	FFD	DT	RC	FR	AFD
ArtificialObjects	Valence	0.224	0.170	0.159	0.083	0.184	0.245
	Arousal	0.177	0.154	0.195	0.169	0.207	0.176
	EDA	-0.329	-0.034	0.162	0.315	0.134	-0.091
	Pulse_Rate	0.272	-0.078	-0.274	-0.285	-0.256	-0.019

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

(7) Ratio of artificial objects

The Table 4.17 results show that, when controlling for the artificial objects ratio, the correlations between artificial objects and valence, arousal, as well as physiological signals (EDA and PR) are weak and not statistically significant. This suggests that artificial objects have a limited impact on these psychological and physiological indicators.

(8) Summary of partial spearman correlation analysis

Partial Spearman correlation analysis results for emotional variables (valence and arousal) showed that shrubs' valence was significantly negatively correlated with TTFF, FFD, and AFD. Grass' arousal was significantly positively correlated with TTFF. No significant correlations were observed between any eye-tracking measures and valence or arousal for other elements when controlling for other landscape elements. These results suggest that, in terms of eye-tracking measures, shrubs and grass have the most significant impact on emotional responses (valence and arousal). Partial Spearman correlation analysis results for physiological signals (EDA and PR) showed that trees' EDA was significantly negatively correlated with FFD, DT, FR, and AFD. Flower trees' EDA was significantly negatively correlated with TTFF, FFD, and AFD. No significant correlations were observed between any eye-tracking measures and EDA or PR for other elements when controlling for other landscape elements.

Visual behavioral differences in different landscape elements

Multivariate models included element proportions as covariates to analyze the impact of element types on visual behavior and to determine differences among various elements. Statistical analysis using the Kruskal-Wallis H test indicated significant differences in TTFF, FFD, RC, DT, FR, and AFD across different landscape elements within urban settings. Boxplot comparisons revealed different patterns of visual attention and cognitive engagement with these elements (Figure 4.4). According to TTFF and FFD, water landscapes are perceived more quickly

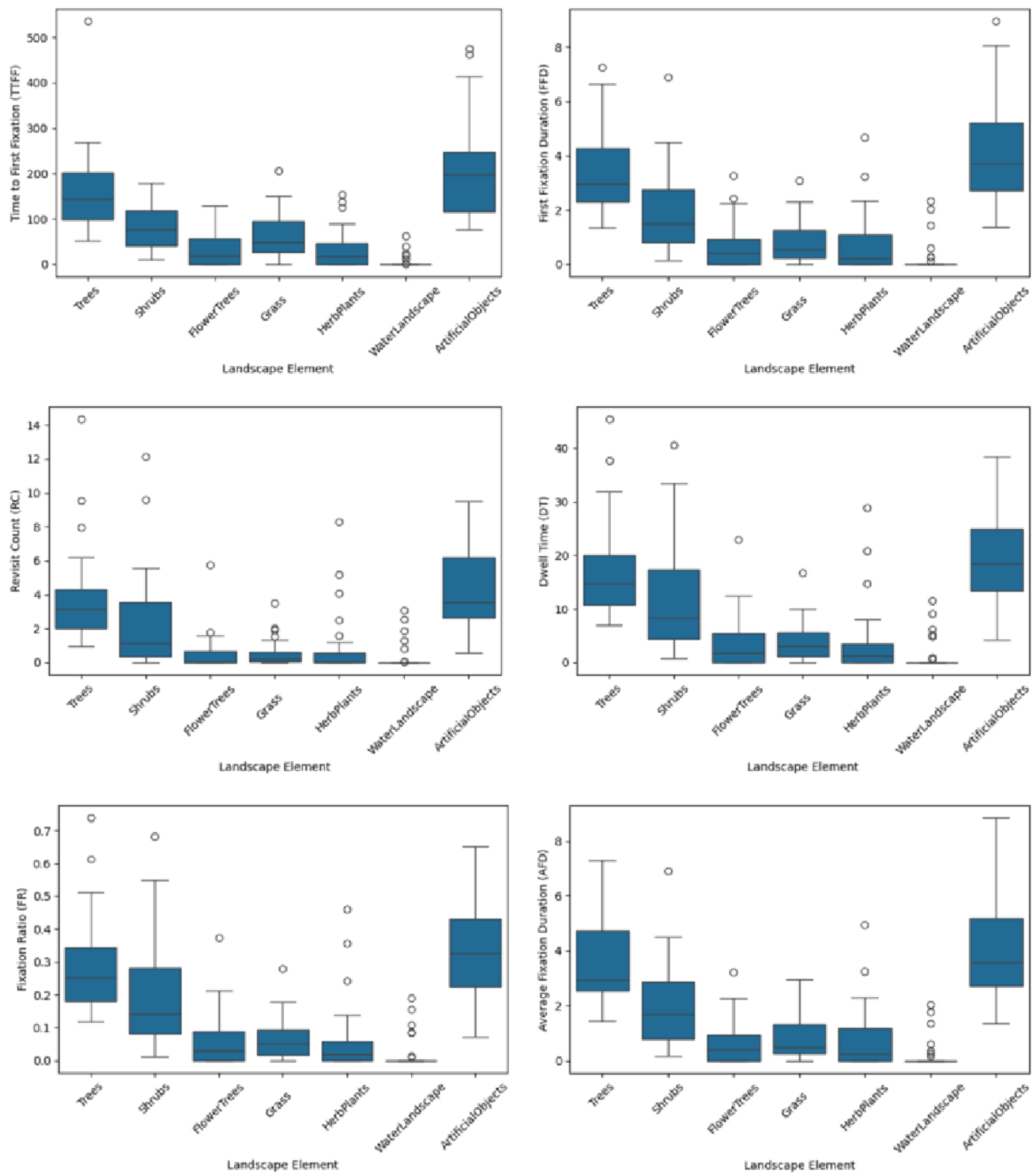


Figure 4.4: Boxplots of participants' visual behavior towards different landscape elements.

Table 4.18: Comparative analysis of physiological responses between two scenes.

	Scene	Mean	Statistic	p-Value
EDA	12	54.23	1423.5	0.048
	29	66.78		
PR	12	79.65	0.160	0.873
	29	79.35		

EDA ranks. Significant if $p < 0.05$ (Mann-Whitney U). PR: mean ± SD. No significant difference if $p > 0.05$ (T-test).

but have shorter initial fixation durations. Artificial objects require more time to initially attract observers' attention, but once attracted, observers tend to engage in longer preliminary processing on these elements. Thus, water landscapes are more appealing but less cognitively complex. According to RC and DT data, artificial objects had the most revisits and showed the longest dwell times. According to FR and AFD data, they exhibited high fixation ratios and long average fixation durations. These results suggest that in virtual environments of urban parks, artificial elements are attractive and more complex but take longer to initially attract observers' attention. In contrast, water landscapes are also appealing but less cognitively complex, and are perceived the fastest.

4.3.3 Eye-tracking emotional responses to landscape elements

When assessing the emotion scores of the individual scenes in the urban park, scene 29 stood out with the highest combined mood score (Combined Score = 4.02), representing the best emotion stimulation.On the contrary, Scene 12 had the lowest emotional score (Combined Score = -0.95) and represented the worst emotionally stimulating space. With this comparison, we further analyzed the eye tracking data of these two scenes to reveal landscape elements that positively or negatively influenced emotional.

Physiological effect in varied emotional spaces

Tests for normality and homogeneity of variance revealed that EDA data do not follow a normal distribution and exhibit unequal variances, whereas PR data are normally distributed with equal variances. Consequently, the non-parametric Mann-Whitney U test will be applied to the EDA data, while an independent samples t-test will be utilized for the PR data. Table 4.18 indicates a statistically significant difference in EDA between the two scenes. Specifically, Scene 12 has an average rank of 54.23 compared to Scene 29's average rank of 66.78, suggesting

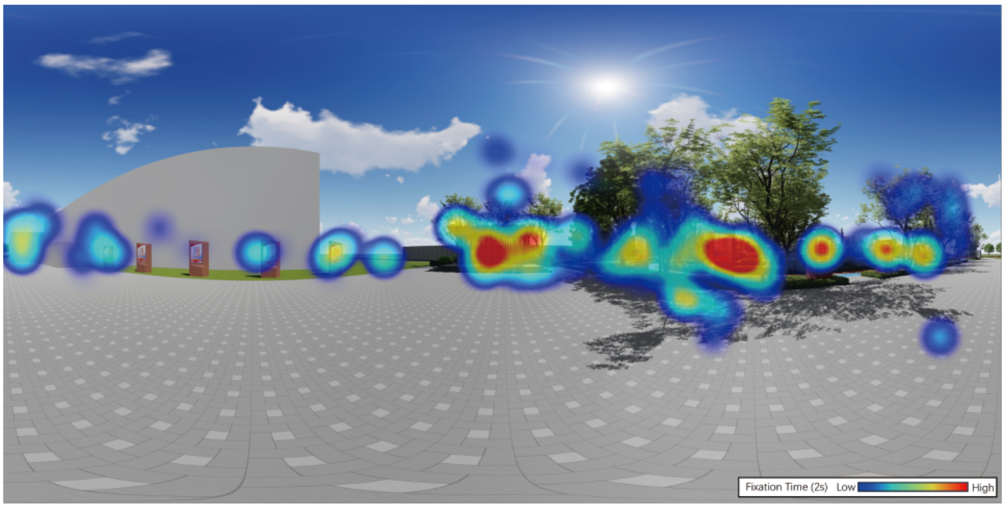


Figure 4.5: Heat map of scene 12.

a more pronounced physiological stress response in Scene 29. This implies that Scene 29 contains elements that may trigger stronger physiological stress responses in participants. However, the t-test statistic for PR is 0.160 with a p-value of 0.873, indicating no significant differences in PR between Scenes 12 and 29.

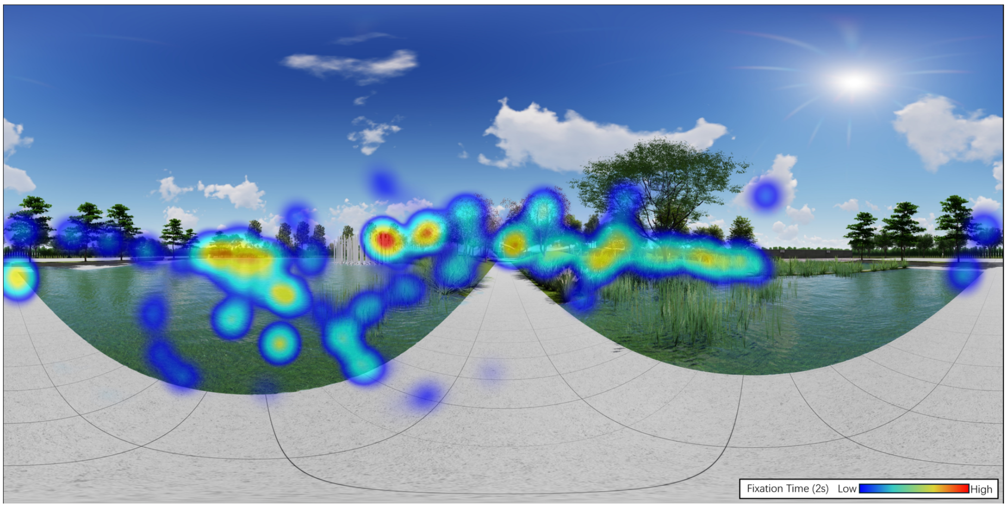


Figure 4.6: Heat map of scene 29.

Eye tracking patterns in negative emotional spaces

In scenes that most effectively elicited positive emotions (Figure 4.5), the eye tracking data reveal a predominant focus on water landscape and herb plants. The corresponding hotspot maps displayed dense red and yellow areas, indicating prolonged visual engagement with these natural elements, which played a key role in evoking positive emotional responses.

Eye tracking patterns in positive emotional spaces

In the scenes associated with the strongest negative emotional responses, eye tracking data reveal a significant focus on artificial objects (Figure 4.6). Hotspot maps displayed intense red and yellow zones, indicating that artificial objects were the primary focus of visual attention, which in turn contributed to negative emotional responses.

4.4 Discussion

4.4.1 Landscape element proportions, emotion responses, and visual behavior

We examined the impact of landscape element proportions on psychological and physiological changes in emotions. Psychologically, herb plants significantly promote positive emotional responses, correlating positively with both valence and arousal. This finding aligns with previous research emphasizing preferences for and emotional perception of ornamental plant species within urban park spaces [88]. In contrast, although shrubs are natural elements, an increase in their proportion tends to reduce emotional arousal. This result contradicts the expectation that shrubs enhance positive emotions [173]. Our investigation into spaces containing shrubs suggests that the dense layout of shrubs may limit visibility, thus reducing arousal levels [174]. Shrubs are a vital element in enhancing the emotional dimensions of LVQ, and their spatial arrangement must be carefully considered to maximize their positive emotional impact.

Physiologically, the proportion of FlowerTrees correlates positively with EDA and negatively with PR, indicating complex physiological responses triggered by these elements [131, 175, 176]. Further integrating eye-tracking data analysis, we observed a positive correlation between the proportion of FlowerTrees and EDA, yet no correlation with eye-tracking metrics. This suggests that physiological responses, such as an increase in EDA, can be decoupled from visual behaviors such as eye movements [177]. FlowerTrees may trigger rapid physiological activation through their color and appearance, which may not directly translate into changes in visual behavior.

Furthermore, In landscape architecture design, fundamental elements such as plant materials, buildings, pavements, and water landscapes play pivotal roles [178]. In our study, we further categorize urban parks into seven elements based on people's visual perception. Our findings confirm that varying proportions of these landscape elements significantly influence both visual engagement and emotional responses in urban parks. We found that apart from the lack of correlation between FlowerTrees and eye-tracking metrics, and between Trees and TTFF, other landscape elements show a significant positive correlation with visual behavior. This indicates that visual behavior follows trends in proportional changes; the larger the area, the more information there is to process [179, 180]. Although there are no significant differences between elements, water landscapes and herb plants more rapidly capture attention, likely due to their unique visual appeal [66].

4.4.2 Landscape element types, emotion responses, and visual behavior

This study shows that artificial objects in urban parks initially capture observers' attention for longer periods, demonstrating higher visual appeal and complexity. This finding aligns with previous research which suggests that while natural elements such as trees and shrubs appear to attract more initial attention, the actual proportion of attention dedicated to artificial objects like street lamps, distant buildings, and benches is significantly higher [85]. In contrast, water landscapes, while also visually appealing, have a lower cognitive complexity and are perceived more quickly. As important components of urban green, water landscapes effectively stimulate positive feedback as observation time increases [56, 181].

Eye-tracking technology revealed that landscape perception is mediated by various visual characteristics. Psychologically, in terms of emotional impact, shrubs, grass, herb plants, water landscapes, and flowering trees were the main influences on emotional scores, while artificial objects and trees had minimal effects. Visual behaviors associated with herb plants correlated positively with emotional enhancements, likely due to their diverse sensory qualities and color variations. Previous studies have also shown that flowering plants are more attractive to observers than green foliage plants [85]. Visual behaviors related to shrubs negatively correlated with emotions (valence and arousal), possibly due to the negative visual preference caused by their dense and obscuring foliage [174]. These results suggest that not all natural elements uniformly enhance emotional responses and that their design and arrangement require careful consideration to optimize emotional benefits and maintain LVQ.

Moreover, eye movements triggered by water landscapes positively correlated with valence, enhancing feelings of pleasure [66, 99, 182]. Generally, flowering trees were negatively correlated with arousal levels, suggesting a calming effect on observers [131]. The TTFF on grasses positively correlated with arousal, indicating that initial engagement or interest in grasslands excites observers, as lawns provide opportunities for walking, playing, and lying down [127, 183]. Controlling for other factors, visual behaviors triggered by shrubs and grasses independently had a significant impact on emotional responses. Physiologically, while all landscape elements had insignificant effects on EDA and PR, trees and flowering trees exhibited a negative correlation with EDA after controlling for other factors, suggesting that these elements might play a role in reducing physiological arousal [53, 101]. These results demonstrate the complex relationship between emotional responses at psychological and physiological levels, and how landscape elements influence these responses through different mechanisms. These findings demonstrate how visual and emotional responses to specific landscape elements contribute to the broader perception of LVQ in urban parks.

4.4.3 Visual behavior in emotional spaces

Our analysis highlights significant differences in the emotional and physiological responses elicited by various elements within urban park landscapes. The physiological data corroborate these findings, offering actionable insights through eye-tracking patterns observed in scenes with both positive and negative emotional ratings. Notably, intense focus on water landscapes and herb plants substantiates their role in enhancing emotional responses [184]. Prolonged attention and concentrated hotspots in these areas not only reflect an intrinsic appeal but also align with biophilic design principles advocated in urban planning [83, 134], demonstrating how these elements stimulate positive emotions while potentially intensifying the sympathetic nervous system's activity [175].

In spaces perceived negatively, artificial objects emerge as focal points, underscoring the potential adverse impacts of poorly integrated or dominant artificial features within green spaces [147, 185]. These findings indicate that the presence of certain artificial objects might diminish the natural benefits typically offered by urban parks, necessitating strategic placement and thoughtful design to mitigate negative emotional reactions. Furthermore, the absence of significant differences in PR between scenes suggests that visual elements do not uniformly affect all physiological markers, highlighting a subtle yet complex relationship between visual stimuli and physiological responses. By identifying these relationships, this study contributes to a deeper understanding of how emotional and physiological responses shape the perception of landscape visual quality.

4.5 Summary

This research focused on the emotional dimension of LVQ. This study quantifies how seven landscape elements influence emotional responses and visual behavior.

Addressing the challenge of low-quality green space provision in compact urban environments, this study investigates how different landscape element proportions and types influence emotional responses and visual behavior through a controlled virtual reality experiment. By integrating physiological signals, eye-tracking, and questionnaire data, we establish a data-driven framework to assess the interplay between landscape elements, visual behavior, and emotional responses. Herb plants most effectively promote both psychological and physiological emotional responses, making them the most emotionally beneficial natural element. Shrubs and artificial objects are associated with negative emotional responses, requiring careful proportion and spatial arrangement. Flowering trees simultaneously decrease pulse rate and increase skin conductance, indicating a compound emotional state of calmness and alertness. To support emotional restoration, designated restorative zones are recommended to minimize artificial elements and incorporate water features and herb plants. This research provides evidence on the specific roles different landscape elements play in influencing human emotional states and visual behavior, both of which are integral to LVQ. By understanding the intricate relationship between landscape elements and human responses, urban environments can be designed to not only fulfill aesthetic and recreational needs but also to support emotional health. By focusing on the emotional aspects of LVQ, this study complements the perceptual insights from Study 1, bridging the gap between perception and emotion in urban park design. The findings aim to provide practical recommendations for designing urban parks that not only satisfy visual and functional needs but also foster positive emotional experiences.

Chapter 5

Emotional and stress recovery dimensions of landscape visual quality

5.1 Introduction

This chapter focuses on children as a specific user group and expands the investigation of landscape elements to examine the emotional and stress recovery dimensions of landscape visual quality (LVQ). The decision to center this study on children is based on several considerations. First, children perceive and evaluate landscape elements differently than adults. For example, a photo-projective study comparing perceptions of a river environment in Japan found distinct differences between child and adult residents, underscoring the need for age-specific design considerations [31]. Second, while the effects of natural environments on adult emotions and stress have been extensively studied—including factors like tree cover and gender differences [32], and virtual nature's influence on youth and seniors [33]—research on children's emotional and stress regulation through environmental interaction remains limited. Third, although environmental features have been shown to support children's creativity and social development [34], urban environments often overlook their needs [35]. Furthermore, existing studies on children's emotional and stress responses to landscapes often rely on indirect or observational methods, such as ethnographic interviews, attention tests, or parental reporting. As shown in previous research [186–188], common approaches include controlled walks, interviews, and self-reported questionnaires. While informative, these methods may lack real-time accuracy and are limited in capturing subtle emotional variations in children. Few studies have employed direct, multimodal measures—such as facial emotion recognition or combined psychological scales—to assess children's affective responses in a controlled experimental setting. This methodological gap highlights the need for more child-friendly, objective tools to evaluate how specific landscape features impact children's emotional states and stress recovery.

In this study, LVQ is investigated through the lens of children's emotional regulation and stress recovery. Specifically, we explore how the composition and proportion of landscape elements—such as openness, greenery, and road ratio—affect children's emotional well-being. A mixed-method approach is used, combining facial emotion recognition with the State-Trait Anxiety Inventory (STAI-S) and the Perceived Restorativeness Scale for Children (PRCS-C II), to assess children's responses more objectively and robustly. Urban parks are recognized as key infrastructure that supports both environmental sustainability and public health. For children, high-LVQ environments are especially valuable in mitigating psychological stress and enhancing emotional well-being, given the growing academic, social, and familial pressures they face in modern urban contexts [25]. Yet, the specific relationship between landscape types, LVQ, and children's emotional outcomes remains underexplored. Traditional methods—such as surveys, observations, and parental interviews—have offered insights into children's emotional states, but they often rely on indirect inference. Technological advances, especially in facial emotion recognition, offer promising tools for capturing children's emotions in real-time, reducing observer bias and enhancing accuracy.

This study integrates qualitative and quantitative methods to evaluate how different urban park landscape types support stress recovery and emotional regulation in children. The sub-objectives of this study are as follows:

- To explore whether different landscape types can alleviate stress in children.
- To explore differences in the effects of different landscape types on children's stress recovery and emotion.
- To explore the relevance of landscape elements to children's stress recovery and emotion.

5.2 Method

5.2.1 Sites selection

Based on the "Urban Green Space Classification Standards," this study selected three urban spaces with high utilization rates by children: a comprehensive park, a children's park, and an urban square. The selected sites were Dalian Labor Park, Children's Park, and Zhongshan Square in Northeast China (Figure 5.1). These sites were chosen for their unique landscape features, which represent a diverse range of green spaces frequently visited by children. Labor Park, with its large area and lush natural environment, features prominent plant arrangements and aesthetic viewing experiences. Children's Park offers abundant vegetation and various play facilities tailored to children's activities. Zhongshan Square, as a typical public square, is spacious with simpler plant arrangements, allowing for the study of urban square features.

This study employed video stimuli instead of on-site experiments to create a controlled and consistent experimental environment, which is essential for isolating the impact of landscape elements on children's emotional and stress recovery. Video stimuli eliminate external variables such as weather, noise, and unexpected interactions that might arise during on-site experiments. Moreover, videos ensure that all participants experience the same environmental conditions, enhancing the reproducibility and reliability of the findings. This approach simplifies logistical procedures while minimizing potential stress for child participants, thereby enhancing the study's ethical and practical feasibility. Importantly, this method enabled better control over environmental distractions during data collection, which is particularly beneficial for capturing children's facial emotional expressions with higher accuracy and less interference. To ensure consistency in environmental conditions, video footage was captured using the GoPro Hero11 Black camera, following a standardized filming route and duration. Each simulated walking video lasted 5 minutes, filmed from a height of 1.60 meters to replicate a child's perspective. Filming was conducted during clear, windless mornings from May 24 to 30, 2023, with original audio retained to simulate real-world conditions (Figure 5.1).

Figure 5.1: Video roadmap and devices. Base map data © OpenStreetMap contributors.

5.2.2 Facial emotion recognition

Given the challenges of equipping children with physiological signal detectors, this study employed facial emotion recognition technology to collect emotional data. Facial photographs were captured every five seconds from recorded videos, resulting in a dataset of 4,416 facial images across the stress and recovery phases. These images were analyzed using the MEGVII Facial Emotion Recognition API, which identifies seven primary emotions: happiness, calmness, surprise, sadness, disgust, anger, and fear. This approach allowed for the construction of an objective, data-driven facial emotion dataset for further analysis.

5.2.3 Quantifying landscape elements

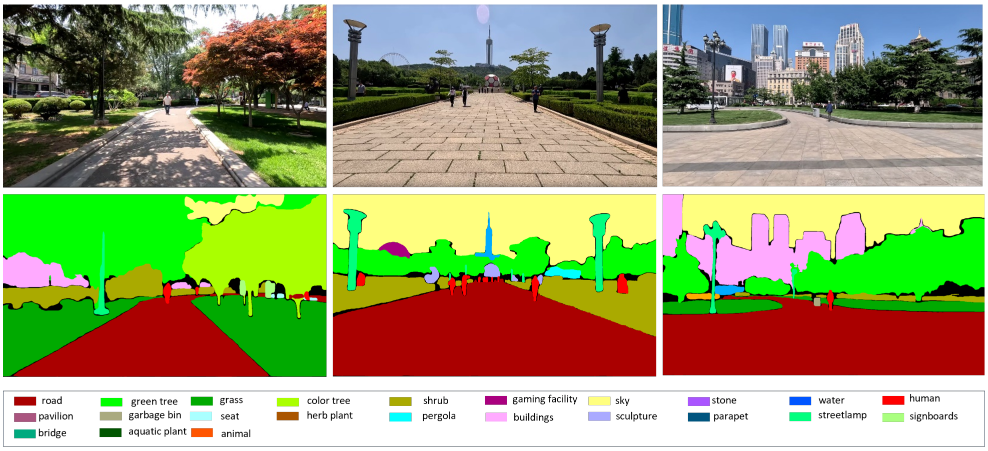


Figure 5.2: Image semantic segmentation examples.

In this study, frames from the video were intercepted every 30 seconds and the proportion of plant and non-plant elements in each photo was calculated, while the background buildings outside the scene were excluded from the statistical analysis due to low relevance to this study. Plant elements were categorized into green-leaf trees, colored-leaf trees, shrubs, grass, and plants. Non-plant elements included water, sky, hardscape, visual dominant elements, and pedestrians. The hardscape included features like a road, gaming facility, parapet, pavilion, and bridge. Visual dominant elements encompassed items such as garbage bins, streetlamps, signboards, seats, pergolas, sculptures, buildings, and stone. Pedestrians included passersby, dog walk-ers, and other users of the landscape space. Separating animals and pedestrians facil-itates the analysis of the impact of these features in the scenes. The obtained images were subjected to image semantic segmentation using the Segment Anything Model [119]. Figure 5.2 illustrates a schematic diagram of semantic segmentation.

5.2.4 Data collection

A total of 18 participants (9 males and 9 females) aged 7–15 years were recruited online, meeting the inclusion criteria of no physical or psychological health issues and no medication use before the experiment. Two participants withdrew during the Trier Social Stress Test (TSST), resulting in valid data from 16 participants (8 males and 8 females). The experimental procedure involved two phases: a stress

Figure 5.3: Experimental procedures and participants.

phase induced by the TSST and a recovery phase facilitated by landscape videos. Participants completed the State-Trait Anxiety Inventory (STAI-S) during both phases, and the Perceived Restorativeness Scale for Children (PRCS-C II) during the recovery phase. Randomized video orders ensured unbiased results. The entire experiment lasted approximately 40 minutes per session, conducted over three days for each participant between July 15 and August 20, 2023. Ethical approval was obtained from the China Children's Center, and parental consent was secured for all participants (Figure 5.3).

5.2.5 Data analysis

1. t-test The anxiety questionnaire scores follow a normal distribution, suitable for comparing the means of two related samples (the same group of children under different conditions). In this case, a paired t-test is used to analyze the data from the stress and recovery periods.
2. Friedman Test The facial emotion data are non-normally distributed, hence the non-parametric Friedman test is used. This test analyzes whether there are significant differences across seven emotional dimensions among three landscape types and is suitable for handling related or paired samples. Additionally, the Friedman test effectively analyzes repeated measures design data to evaluate if there are significant differences in medians under different

Figure 5.4: 16 experimental participants.

conditions.

3. Bivariate Correlation Analysis To explore the relationship between landscape spatial features and stress recovery and emotional responses, this study conducts a bivariate correlation analysis between the quantitative values of landscape features for three types and participants' PRCS-C IIscores and mean emotional difference values.
4. One-way ANOVA A one-way ANOVA is conducted on three landscape features: green trees, shrubs, and sky, to determine which landscape features positively influence children's emotional experiences and stress recovery. One-way ANOVA is used to compare the mean differences between three or more groups to determine if at least one group differs significantly from the others.

5.3 Results

5.3.1 Evaluation of stress responses and emotional changes

Stress Response

Based on the results from the paired sample t-test (Figure 5.5), all three

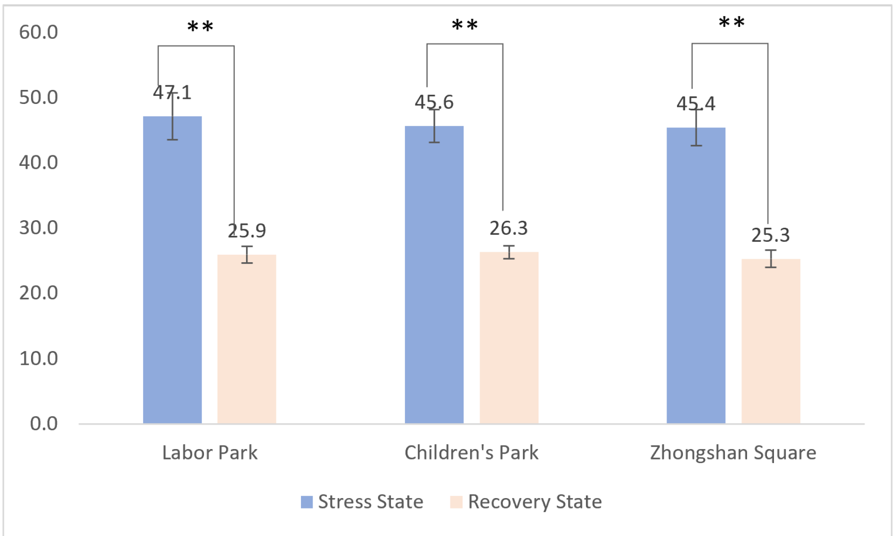


Figure 5.5: Changes in STAI-S values from the stress stage to the recovery stage (n=16).

** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$).

landscape types significantly reduced the anxiety levels in children. During the post-stress state and the stress recovery state, there was a significant difference in anxiety scores, and the difference was statistically significant ($p < 0.01$).

Emotional Change

In this study, we assessed the impact of different landscape types on children's emotional recovery from stress. We compared the emotional changes and significance of three different landscape types in children's transition from a stress state to a recovery state through line graphs and Wilcoxon tests (Figure 5.6, Figure 5.7, Figure 5.8). The results of the Wilcoxon test indicate that, in Zhongshan Square, children exhibited significant recovery effects across four emotional dimensions: "Happiness" ($p < 0.05$), "Calmness" ($p < 0.01$), "Surprise" ($p < 0.01$), and "Disgust" ($p < 0.01$). Notably, the significant increase in "Calmness" during the stress recovery state, along with the significant decreases in other emotions, suggests that Zhongshan Square provides an environment conducive to children's emotional regulation and recovery. A slight decrease in "Happiness" during the recovery phase in Zhongshan Square may be attributed to specific environmental factors or the nature of the recovery process. The exact reasons for this decreased need to be explored in future research, highlighting the complexity of emotional responses during stress recovery.

In the Children's Park, significant changes were observed in "Calmness" (p

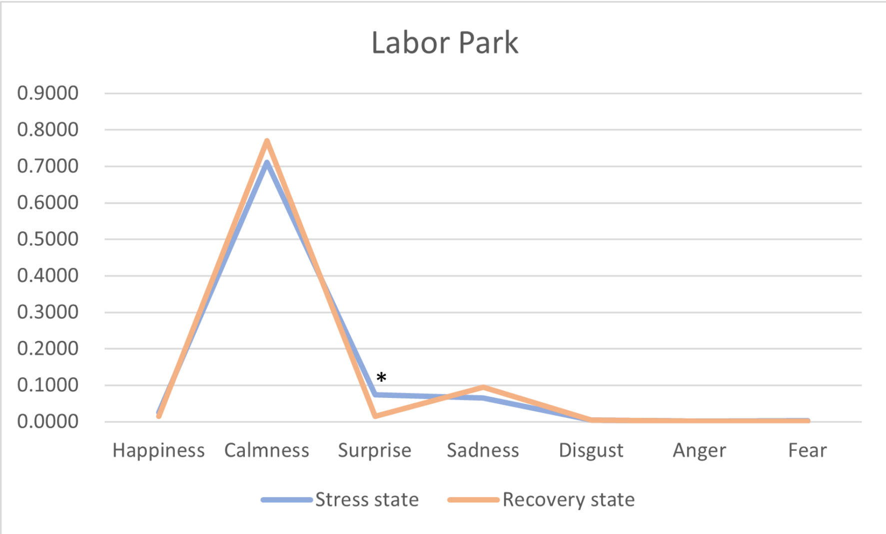


Figure 5.6: Comparing changes in children's emotion during labor park stress and recovery states.

N = 16, median, ** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$), Wilcoxon test.

< 0.05) and "Disgust" ($p < 0.05$), indicating that the park promotes children's calmness while alleviating feelings of disgust. Changes in "Happiness" (p=0.056) and "Surprise" (p=0.063) did not reach traditional significance levels, but p-values approaching 0.05 suggest a potential trend, indicating that further research may provide more insights into these two emotional dimensions.

Labor Park showed significant statistical changes in "Surprise" ($p < 0.05$). However, the role of "Surprise" as a neutral emotion during the recovery process remains unclear, emphasizing the need for further investigation into this complex emotional response.

Overall, the findings of this study suggest that urban landscape environments have different impacts on children's emotions. Zhongshan Square exhibited the most significant recovery effects across multiple emotional dimensions, while Children's Park and Labor Park also demonstrated positive effects in specific emotional aspects. These insights are crucial for urban planners and public space designers, emphasizing the importance of considering the emotional impact of different environments when creating spaces that contribute to children's psychological well-being.

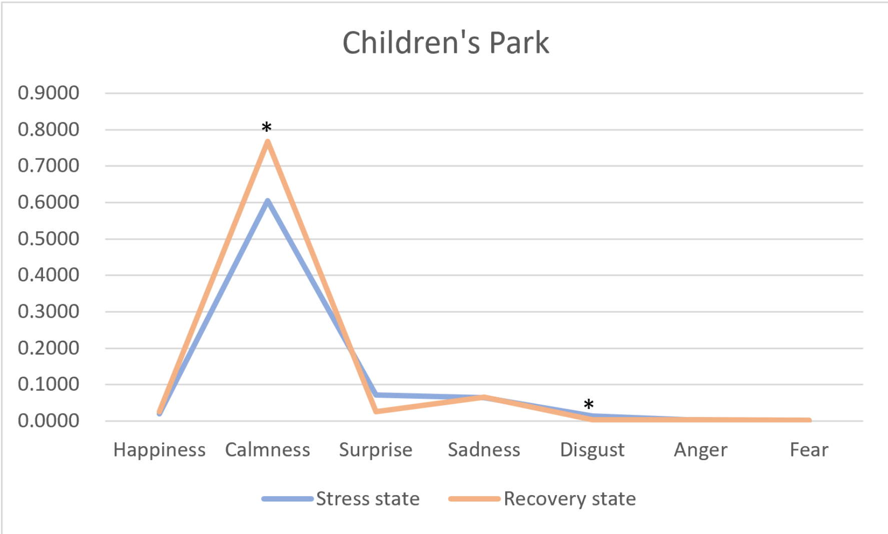


Figure 5.7: Comparing changes in children's emotion during children's park stress and recovery states.

N = 16, median, ** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$), Wilcoxon test.

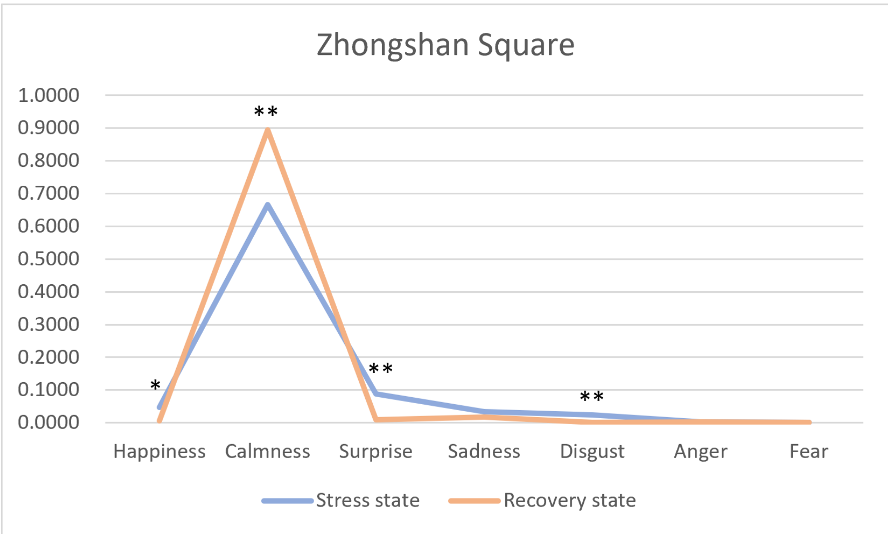


Figure 5.8: Comparing changes in children's emotion during Zhongshan square stress and recovery states.

N = 16, median, ** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$), Wilcoxon test.

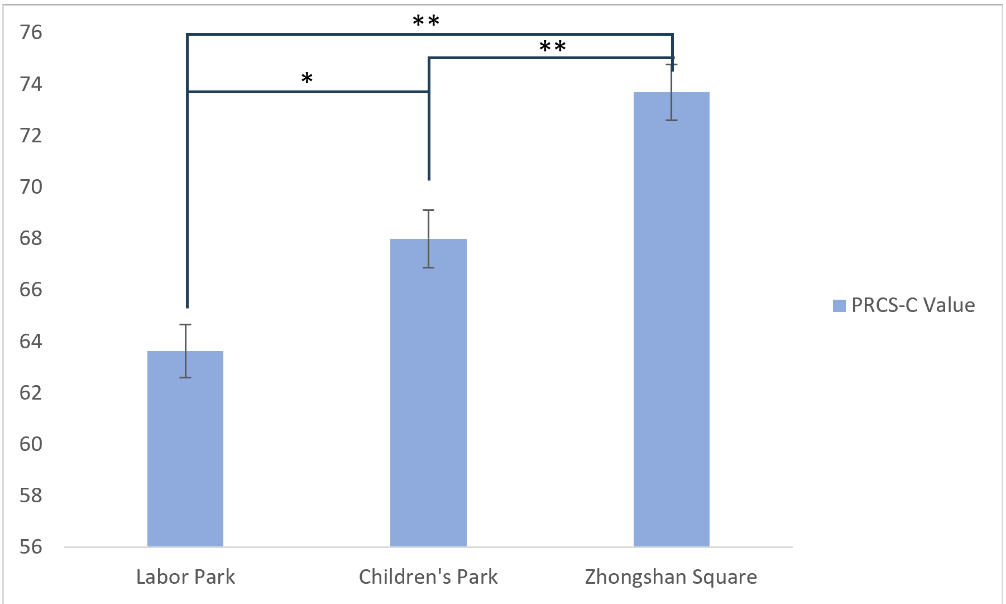


Figure 5.9: Comparison of perceived restrictiveness of different landscape types.

N=16, mean±SEM, ** Significant at the 99% level ($p < 0.01$), * Significant at the 95% level ($p < 0.05$), Wilcoxon test.

5.3.2 Effect of landscape types on children's stress recovery and emotion

Differences in perceived restorativeness across landscape types

Upon examining the PRCS-C IIscores, it was observed that for the landscapes of Labor Park, Children's Park, and Zhongshan Square, all associated PRCS-C IIvalues were positive (Figure 5.9). This indicates that children perceived all three landscapes as having a beneficial impact on their psychological recovery. Results from a one-way ANOVA demonstrated significant differences in PRCS-C IIvalues among the three landscapes ($F=21.894$, $p < 0.01$). The highest PRCS-C IIvalue was associated with Zhongshan Square, scoring 73.69±1.091, suggesting that Zhongshan Square offered the most optimal recovery effects. This was followed by Children's Park with a score of 68±1.118, while Labor Park showed the least recovery potential, scoring 63.63±1.024. Post-hoc tests revealed highly significant differences between Labor Park and Zhongshan Square and between Children's Park and Zhongshan Square ($p < 0.01$). A significant difference was also noted between Labor Park and Children's Park ($p < 0.05$). As shown in Table 5.1, it's clear that children perceive distinct restorative differences across the three landscapes. Specifically, Zhongshan Square stands out with the highest score, showcasing the most favorable perceived restorative attributes for children. This is followed by Children's Park. Labor Park, on the other hand, registered the lowest score, indicating a comparatively diminished restorative effect for children in that setting.

Table 5.1: Post-hoc analysis of children's perceived restorativeness across different locations.

(I) Location	(J) Location	Mean Difference(I-J)	Standard Error	p	95% Confidence Interval Lower Limit
Labor Park	Children's Park	-4.375*	1.525	<0.05	-7.45
	Zhongshan Square	-10.062*	1.525	<0.01	-13.13
Children's Park	Labor Park	4.375*	1.525	<0.05	1.30
	Zhongshan Square	-5.687*	1.525	<0.01	-8.76
Zhongshan Square	Labor Park	10.063*	1.525	<0.01	6.99
	Children's Park	5.688*	1.525	<0.01	2.62

Differences in children's emotions across landscape types

In conjunction with the PRCS-C IIassessment, this study combined facial emotion recognition techniques to comprehensively assess the effects of different landscape types on children's emotional responses. As shown in Table 5.2, the application of the Friedman test to analyze seven emotional dimensions (Happiness, Calmness, Surprise, Sadness, Disgust, Anger, and Fear) indicates significant differences in the dimensions of "Happiness," "Calmness," and "Disgust" across three distinct landscape spaces.

Happiness: Significant variations were observed in Happiness levels ($Z=9.375$, $p < 0.01$) among Labor Park, Children's Park, and Zhongshan Square. Post hoc analyses indi-cated that both Children's Park and Zhongshan Square exhibited significantly higher Happiness levels compared to Labor Park ($p < 0.05$). However, no statistically signifi-cant difference in Happiness was found between Labor Park and Children's Park ($p > 0.05$). Calmness: Calmness levels demonstrated significant differences ($Z=9.500$, $p < 0.01$) across the three landscape spaces. Post hoc analyses revealed that Zhongshan Square displayed significantly higher Calmness levels compared to both Labor Park and Children's Park ($p < 0.05$). No significant difference in Calmness was identified between Labor Park and Children's Park ($p > 0.05$). Disgust: The Friedman test indicated significant differences ($Z=9.375$, $p < 0.01$) in Disgust levels among the three landscape types. Post hoc analyses showed that both Children's Park and Zhongshan Square had significantly lower Disgust levels com-pared to Labor Park ($p < 0.05$). No statistically significant difference in Disgust was observed between Labor Park and Children's Park (p >

Table 5.2: Emotional responses across different landscape spaces: results from the friedman test.

Emotion	Labor Park	Children's Park	Zhongshan Square	chi-square	p
Happiness	0.00064 (-0.00030, 0.00437)	**0.01376 (-0.00042, 0.06976) a**	**0.04352 (0.00096, 0.07674) a**	9.375	.009
Calmness	-0.06059 (-0.17958, 0.11550)	-0.06087 (-0.20263, 0.02949)	**-0.25586 (-0.38376, -0.05383) ab**	9.500	.009
Surprise	0.00166 (0.03295, 0.00296)	0.00852 (0.00032, 0.02340)	0.02311 (0.00240, 0.07107)	3.375	.185
Sadness	0.00183 (-0.07118, 0.06548)	-0.01947 (-0.06781, 0.03111)	0.09027 (-0.00772, 0.09027)	2.000	.368
Disgust	-0.00166 (-0.03295, 0.00296)	0.00852 (0.00032, 0.02340)	**0.02311 (0.00240, 0.07107) ab**	9.375	.009
Anger	0.00005 (-0.00815, 0.00079)	0.00037 (-0.00616, 0.00348)	-0.00033 (-0.00506, 0.00320)	1.125	.570

a N=16, "a" indicates a significant difference compared to Labor Park, and "b" indicates a significant difference compared to Children's Park, with pairwise comparisons adjusted using Bonferroni correction.

0.05). In summary, our study findings underscore the impact of different landscape types on children's stress recovery and emotional experiences. Notably, Zhongshan Square consistently emerged as a space that fosters higher levels of happiness and calmness. These results provide valuable insights for urban planning and landscape design, emphasizing the need for environments that positively contribute to children's emotional well-being.

5.3.3 Effect of landscape elements on children's stress recovery and emotion

Impact of landscape elements on stress recovery and emotion

To investigate the relationship between landscape feature elements and stress recovery and emotion. In this study, bivariate correlation analyses were conducted between the quantitative values of landscape feature elements of the three landscape types and the subjects' PRCS-C IIscores, happiness difference means, calmness difference means, and disgust difference means. The results are presented in Table 5.3.

Table 5.3: Relationship between landscape feature elements and physiological and psychological recovery effects.

		Green-leaf Trees	**Colored-leaf Trees**	**Shrubs**	**Grass**	**Plant**	**Water**	**Sky**	**Hardscapes**	**Visual Dominant Elements**	**Pedestrians**
PRCS-C II	Pearson	-.527**	-0.027	-.405*	0.013	-0.246	-0.213	.434*	0.059	-0.003	0.078
	Sig.	0.002	0.879	0.02	0.945	0.168	0.233	0.012	0.745	0.987	0.665
Happiness	Pearson	-.444**	0.054	-.354*	0.074	-0.254	-0.186	0.337	-0.009	0.012	0.114
	Sig.	0.01	0.763	0.044	0.684	0.154	0.300	0.055	0.958	0.949	0.528
Calmness	Pearson	.598**	0.142	.442*	0.075	0.212	0.233	-.535**	-0.15	0.023	-0.021
	Sig.	< .001	0.432	0.01	0.678	0.236	0.191	0.001	0.403	0.897	0.908
Disgust	Pearson	-.431*	0.065	-.345*	0.081	-0.254	-0.182	0.322	-0.019	0.013	0.118
	Sig.	0.012	0.718	0.049	0.652	0.154	0.311	0.067	0.918	0.941	0.512

** Significant correlation at the 0.01 level (two-tailed). * Significant at the 0.05 level (two-tailed).

PRCS-C IIAnalysis: The presence of green-leaf trees (Pearson correlation coefficient = -0.527, $p = 0.002$) and shrubs (Pearson correlation coefficient = -0.405, $p = 0.02$) was significantly and negatively correlated with PRCS-C IIvalues, suggesting that reductions in the presence of green-leaf trees and shrubs in the landscape were asso-ciated with enhanced stress recovery in children. Additionally, sky proportion (Pear-son correlation coefficient = 0.434, $p = 0.012$) exhibited a positive correlation with PRCS-C IIscores. This implies that increasing the sky proportion may further enhance children's stress recovery experiences. These findings provide valuable insights for designing landscapes tailored to children, emphasizing the importance of specific natural elements in promoting the overall well-being of children.

Analysis of Mean Happiness Differences: Mean happiness differences were calculated by subtracting recovery state data from stress state data. Larger differences indicate relatively lower values during the recovery state, while smaller (or possibly negative) differences indicate relatively higher values during the recovery state. This suggests that the mean differences are negatively correlated with happiness during recovery. Green trees (Pearson correlation coefficient = -0.444, $p = 0.01$) and shrubs (Pearson correlation coefficient = -0.354, $p = 0.044$) exhibited a significant negative correlation with mean happiness differences. In contrast, an increase in sky proportion (Pearson correlation coefficient = 0.337, $p = 0.055$) showed a significant positive correlation with mean happiness differences. This indicates that a higher level of happiness in children is associated with more trees and shrubs, and a smaller sky proportion.

Analysis of Mean Calmness Differences: Mean calmness differences were calculated by subtracting recovery state data from stress state data. Larger differences indicate relatively lower values during the recovery state, while smaller (or possibly negative) differences indicate relatively higher values during the recovery state. This suggests that the mean differences are negatively correlated with calmness during recovery. Green trees (0.598, $p < 0.01$) and shrubs (0.442, $p = 0.01$) showed a significant positive correlation with mean calmness differences, while sky proportion (-0.535, $p = 0.01$) exhibited a significant negative correlation with mean calmness differences. These findings indicate that reducing green trees and shrubs and increasing sky proportion is associated with increased calmness during recovery.

Analysis of Mean Disgust Differences: Mean disgust differences were calculated by subtracting recovery state data from stress state data. Larger differences indicate relatively lower values during the recovery state, while smaller (or possibly negative) differences indicate relatively higher values during the recovery state. This suggests that the mean differences are negatively correlated with disgust during recovery. Green trees (-0.431, $p = 0.012$) and shrubs (-0.345, $p = 0.049$)

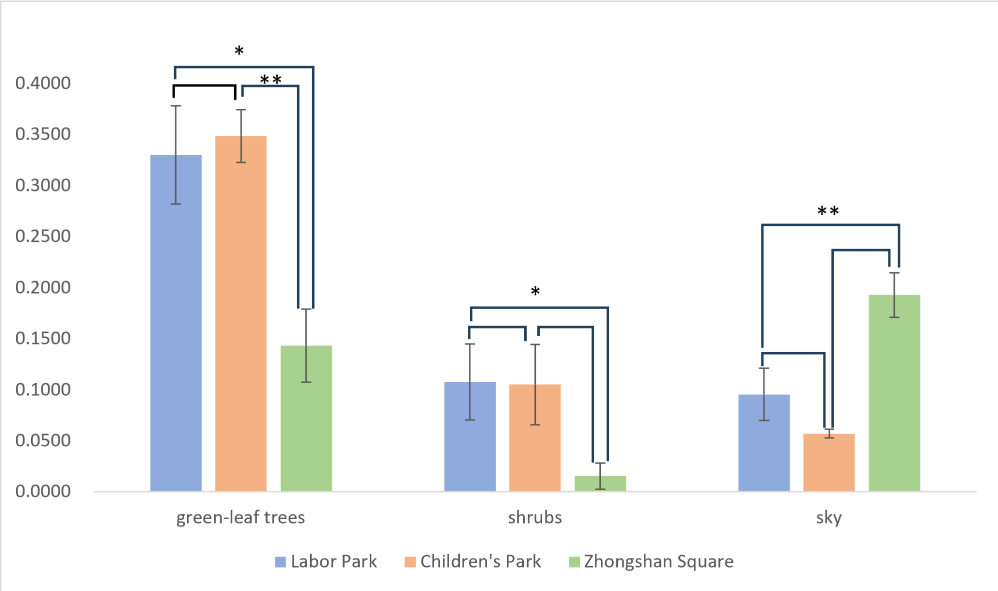


Figure 5.10: Comparison of landscape feature elements.

exhibited a negative correlation with mean disgust differences. This indicates that reducing green trees and shrubs is positively correlated with a decrease in disgust in children during the stress recovery period.

Through the quantitative analysis of spatial characteristics and stress recovery and emotion in Labor Park, Children's Park, and Zhongshan Square, we have understood the effects of green leafy trees, shrubs, and sky on children's stress recovery and emotion, while the three landscape spaces have different effects on children's stress recovery and emotion regulation. The results of one-way ANOVA for each of the 3 landscape spaces Green-leaf Trees, Shrubs, and Sky showed (Figure 5.10). For the Green-leaf Trees indicator, there was no significant difference between Labor Park and Children's Park, while the value of Zhongshan Square was significantly lower. ANOVA results showed significant differences between groups ($p < 0.001$). Shrubs metrics and the mean values of shrubs differed among the three sites. There was no significant difference between Labor Park and Children's Park, while the value for Zhongshan Square was significantly lower. ANOVA results showed a significant difference between groups ($p = 0.037$). For the Sky metric, the difference between Labor Park and Children's Park was relatively small, while the value for Zhongshan Square was significantly higher. The ANOVA results showed a significant difference between groups ($p = 0.002$). The comparison reveals that Zhongshan Square has a higher proportion of sky and relatively fewer leafy trees and shrubs compared to Labor Park and Children's Park. These features may be factors contributing to Zhongshan Square's better performance in terms of children's stress recovery and emotional experience.

Through an in-depth analysis of the relationship between different landscape spatial features and children's stress recovery and emotional experiences, we draw the following conclusions: in landscape design, a higher proportion of sky, and relatively fewer green-leaf trees and shrubs have a positive impact on promoting children's stress recovery, enhancing calmness emotions, and reducing disgust. The presence of more green-leaf trees and shrubs, along with a smaller proportion of sky, correlates with children's happiness.

5.4 Discussion

5.4.1 Effects of different landscapes on children's stress recovery

This study highlights the impact of different landscape types on children's stress recovery and emotional responses [66, 102]. The selected TSST effectively induced changes in state anxiety and facial emotion recognition. Analysis of PRCS-C IIscores revealed that children perceived all three landscapes—Labor Park, Children's Park, and Zhongshan Square—as restorative, consistent with previous studies emphasizing the psychological benefits of green landscapes [189,190]. Interestingly, Zhongshan Square, an urban square landscape, exhibited the highest recovery potential, challenging traditional assumptions about the restorative attributes of green spaces. This finding underscores the importance of considering LVQ as a multidimensional construct that extends beyond greenery to include openness, spatial arrangement, and visual diversity.

The study indicates that the proportion of green-leaf trees and shrubs is significantly negatively correlated with PRCS-C IIscores, while the sky proportion is positively correlated. These results suggest that landscape visual quality is not solely determined by the quantity of green elements but also by their spatial configuration and the perceived openness of the space. Compared to adults, children may be more sensitive to spatial openness, potentially due to differences in developmental stages and cognitive processes [191]. Adults tend to evaluate the visual quality of green spaces based on spatial orderliness and element coordination, such as organized layouts, distinct color contrasts, and well-designed pathways, which are associated with positive perceptions [22]. In contrast, children are more drawn to direct experiences, favoring open spaces that encourage exploration and interaction. These distinctions highlight the importance of designing landscapes that balance openness and greenery to better support children's emotional and stress recovery.

5.4.2 Effects of different landscapes on children's emotion responses

Happiness.

In the current study, the results indicate that different landscape types influence changes in children's happiness. The current findings reveal significant differences in "green-leaf trees," "shrubs," and "sky proportion" in relation to happiness from the perspective of children. More trees and shrubs, and a smaller sky proportion are associated with higher levels of happiness in children. Higher levels of happiness are associated with more green elements and a reduced sky proportion, highlighting the role of greenery in enhancing the emotional dimensions of LVQ. Similar to our study, Reeve et al. [192] concluded in a study on the effects of a rehabilitation garden in a children's hospital that patients spending time in the garden reported higher levels of happiness. They also found that the garden provided emotional relief for visitors through appreciating scenic views, being in nature, enjoying time, therapeutic experiences, and exposure to outdoor air. Van den Berg et al. [193] compared a park-like forest area with an urban environment and found that parks with a high green view rate generated higher levels of happiness and lower levels of stress, anger, depression, and tension during the recovery period, thereby improving emotion. Some studies suggest that children are particularly fond of water features as they can evoke feelings of joy in children [191]. Although in this study, water features did not show a significant correlation with children's happiness, comparing the features of the three landscape spaces, both Labor Park and Children's Park include water features, while Zhongshan Square does not. This may explain why the happiness changes in Zhongshan Square are lower than in the other two landscape spaces.

Calmness.

Enhancing calmness is essential for stress recovery, and this study found that open spaces with a higher sky proportion and balanced greenery contribute to increased calmness. This result aligns with research by Ahmad Hami et al. [194], which highlighted the preference for open and spacious areas in campus landscapes. For children, the emotional dimension of LVQ emphasizes the importance of spatial openness and simplicity over dense or enclosed settings. Open spaces allow for greater flexibility in activities and reduce feelings of restriction, making them more restorative and engaging for children [195].

Disgust.

In the current study, the results indicate that maintaining an appropriate proportion of green-leaf trees and shrubs can effectively reduce children's disgust, positively impacting stress recovery in children. This is consistent with the findings of Simone et al. [196], who investigated the impact of green spaces in the homes of Dutch children on brain structure from birth. They observed a negative correlation between tree coverage density and brain structure in the prefrontal clusters region. In these areas, where trees are more densely concentrated, there may be an adverse impact on the gray matter volume of the prefrontal cortex in children. This suggests that an increase in tree density in these regions may be associated with a negative correlation in the development of brain structures related to cognitive control, emotional regulation, and social behavior in children. In this study, a reduction in green trees and shrubs was positively correlated with a decrease in children's aversion during the stress recovery period. In this study, balanced proportions of greenery reduced aversion during the recovery period, emphasizing the role of LVQ in creating emotionally supportive environments. The negative emotional responses associated with overly dense greenery further highlight the importance of considering both visual diversity and balance in LVQ metrics.

5.5 Summary

This study underscores the value of LVQ as a framework for understanding the relationship between landscape elements and children's emotional recovery. A mixed-method recovery approach, incorporating facial emotion recognition and psychological scales, enabled the evaluation of children's emotional changes in response to landscape features. The study shows that in children's spaces, emotional and stress recovery benefits depend not only on the presence of greenery, but also on its proportion and the degree of openness. While greenery remains important, spatial openness seems to play a more prominent role in shaping children's emotional responses. Landscape spatial features can lead to changes in children's emotions, particularly in terms of "calmness," "happiness," and "disgust." These findings contribute to advancing child-friendly landscape design by emphasizing the need for thoughtful spatial arrangements and visual balance.

Chapter 6

Conclusion, implication, and limitations

6.1 Conclusion

This dissertation investigates how landscape visual quality (LVQ) in urban parks influences human perception, emotional responses, and stress recovery, with a particular focus on the Chinese urban context. Although rapid urbanization in China has led to a significant expansion in the number of urban parks, improvements in their design quality have not kept pace. Many parks fall short of meeting users' psychological and perceptual needs, resulting in underutilization and inefficient resource allocation. In response, this research proposes a multidimensional framework for evaluating and enhancing LVQ, aiming to generate both theoretical contributions and practical guidance for urban park planning and design.

Study 1 focuses on assessing urban park LVQ using multidimensional visual indicators. This study demonstrated the efficacy of VR-based multidimensional visual indicators in enhancing LVQ assessment of urban parks. Using a VR-based multifaceted approach, we developed a set of multidimensional visual indicators to understand the impact of LVQ on human perception of urban parks. Improved model differentiation of positive and negative perceptions by 1–7% using multidimensional visual indicators. The integrated model demonstrated a better fit and distinguished more effectively between positive and negative perceptions compared to models using only spatial feature indicators. Therefore, our integrated model incorporating various multidimensional visual indicators accurately classifies human perceptions of urban park LVQ. Our approach allows for pre-assessment of LVQ before urban park construction, enabling planners to make informed design adjustments early in the process. This study revealed key design elements: Herb plants, water ratio, and number of materials were the most positively correlated indicators (eye-tracking, image segmentation, and spatial feature indicators, respectively) influencing human perception. Second, this study explored the correlations between human perceptions and urban park landscape environments using eye tracking data. Isolated planting styles, which drew the most attention, positively impacted the greenness perception. Perceptions of beauty, complexity, and liveliness were positively correlated with eye-tracking data from herb plants, whereas perceptions of greenness were negatively correlated with the HerbRatio. SkyRatio was negatively correlated with beauty, consistent with the street-level analysis results. Moderate degree of openness (20–80%) positively correlated with beauty, establishing a range for openness. However, high openness led to a monotonous visual landscape, as elements within a 15-meter radius tend to be uniformly sparse, thereby reducing the perceived liveliness of urban parks but enhancing the perception of safety. Shrub species diversity enhances perceptions of greenness and complexity by enriching vegetation richness and visual complexity. In contrast, low shrub species diversity, as reflected in dwell time to shrubs, suppresses greenness perception. Additionally, dense shrubs can obstruct open views and limit the visibility of other landscape elements, which may reduce perceptions of liveliness. The framework not only allows for a detailed understanding of how urban park elements influence perceptions but also provides a practical tool for urban planners and designers to pre-assess and refine park designs, aligning them with user expectations and minimizing resource inefficiencies.

Study 2 expanded the investigation into the emotional dimensions of LVQ, analyzing how landscape elements influence emotional responses and visual behavior. This study demonstrates that landscape elements within urban parks significantly influence emotional responses and visual behavior. By integrating visual behavior metrics with physiological and self-reported emotional data, this study offers practical, data-driven guidance for designing emotionally supportive urban parks. Designers are recommended to minimize visually dominant artificial structures in emotionally restorative areas, while strategically incorporating sensory-rich elements such as herb plants and water landscapes to enhance visual engagement and psychological benefits. Specifically, urban park designers are encouraged to emphasize visually prominent herb plants and water landscapes to foster positive affect and support restorative engagement, while avoiding overly dense shrubs or large clusters of artificial structures that may introduce visual clutter. A moderate use of flowering trees can create aesthetically pleasing focal points while balancing arousal and relaxation. Together, these strategies can enhance the psychological benefits of urban parks, contributing to urban residents' overall well-being. These results highlight that different landscape elements contribute uniquely to the emotional experience and LVQ of urban parks.

Study 3 introduced a child-specific perspective on LVQ, addressing the unique needs of this user group while maintaining a focus on emotional regulation and stress recovery. The study shows that in children's spaces, emotional and stress recovery benefits depend not only on the presence of greenery, but also on its proportion and the degree of openness. While greenery remains important, spatial openness seems to play a more prominent role in shaping children's emotional responses. Additionally, landscape spatial features were shown to influence children's emotional states, particularly in terms of "calmness," "happiness," and "disgust." The research highlights that certain natural elements, such as water features and herb plants, are more likely to elicit positive emotional responses, while artificial objects, despite their visual appeal, may evoke negative emotions. These results emphasize the nuanced contributions of different landscape elements to emotional experiences, underscoring the need for targeted strategies that prioritize emotional well-being in landscape design. By integrating insights from children's emotional responses, this study broadens the application of LVQ to inform inclusive and adaptive urban park designs that cater to diverse user needs.

By integrating these findings with the broader goals of sustainable urban development, this dissertation offers practical and evidence-based recommendations for urban planners and designers in China and beyond. The emphasis on LVQ as a multidimensional framework not only bridges the gap between aesthetic appeal and emotional well-being but also aligns with global sustainability objectives. Moreover, the inclusion of child-specific insights enriches the applicability of this framework, underscoring the importance of designing inclusive urban parks that cater to diverse user needs. Ultimately, this research provides a comprehensive pathway for creating urban parks that balance functionality, visual quality, and restorative benefits, contributing to the physical and psychological health of their users while advancing the practice of sustainable urban design.

6.2 Research implications

6.2.1 Theoretical implications

This research utilizes multidisciplinary technologies to analyze urban landscapes, fundamentally advancing the theoretical framework of environmental psychology. By integrating eye-tracking technology and image segmentation within a virtual reality environment, this study provides a novel multidimensional framework for evaluating urban LVQ. It comprehensively captures human visual perception and cognitive responses.

Key theoretical advancements include:

1. Reconceptualization LVQ as a multidimensional construct. This study redefines LVQ as a multidimensional construct. By demonstrating how these dimensions contribute to both positive and negative perceptions, this research provides a more nuanced understanding of LVQ, positioning it as a

critical metric for evaluating urban park quality. The developed classification models, which integrate spatial, visual, and cognitive indicators, outperform traditional indicator-based models, offering a significant theoretical contribution to environmental psychology and landscape design.

2. Establishment of links between emotions and visual behavior. This research quantifies the relationship between landscape features and emotional responses, mediated by visual attention. It demonstrates how landscape elements, such as herb plants and water features, evoke positive emotional responses, while shrubs and artificial objects may elicit negative reactions. This provides a deeper theoretical understanding of the role visual behavior plays in emotional regulation within urban environments. By linking LVQ to measurable emotional dimensions, the study bridges a critical gap in the environmental psychology literature, advancing theories on how landscape elements influence human emotions through visual stimuli.

3. Expansion of LVQ to child-centric frameworks. Through the inclusion of experiments focusing on children, this research extends the theoretical scope of LVQ to address the needs of younger and often overlooked user groups. The findings highlight that openness and greenery proportions are key factors in creating emotionally supportive environments for children, providing a foundation for child-centered LVQ theories. This contribution emphasizes the adaptability of LVQ to diverse demographic needs, offering a more inclusive theoretical model for urban landscape design.

4. Methodological integration of multimodal data. By employing cutting-edge technologies such as eye-tracking and facial emotion recognition within a VR environment, this dissertation introduces a comprehensive approach to LVQ assessment. Traditional methods, including questionnaire-based evaluations, often lack the precision to capture the dynamic interactions between users and landscapes. The integration of multiple data collection techniques enables a more accurate, objective, and reproducible analysis of how landscape elements influence perception, emotion, and stress recovery. This approach contributes to the theoretical advancement of LVQ research by offering data-driven insights into human-environment interactions.

5. Advancement of evidence-based design principles. The dissertation contributes to the broader discourse on evidence-based urban design by establishing LVQ as a critical theoretical and practical tool. It not only validates the importance of balancing natural and artificial elements in urban parks but also provides a theoretical framework for integrating user-centered perspectives into the planning and design process. This positions LVQ as both a theoretical and operational construct, capable of guiding sustainable and user-responsive urban development.

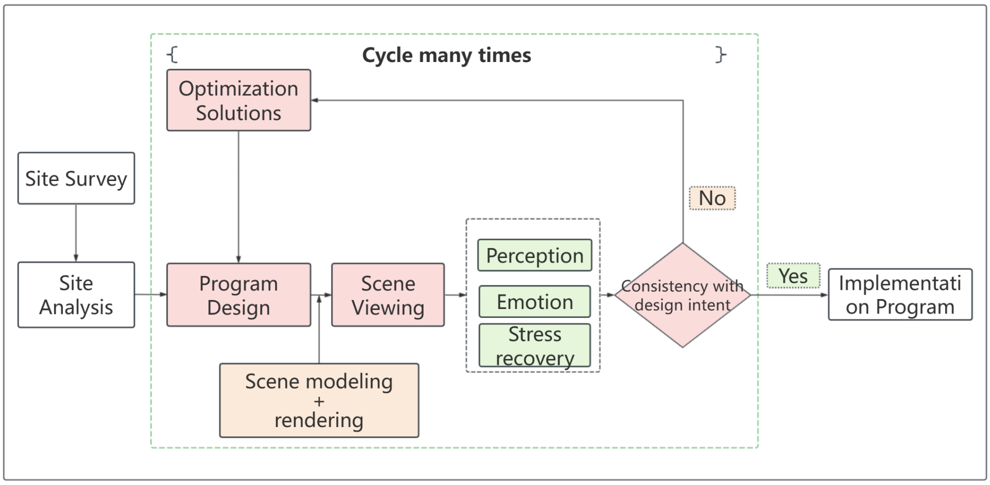


Figure 6.1: Landscape program evaluation process.

6.2.2 Practical implications

This dissertation presents an integrative framework for assessing and enhancing LVQ in urban parks, specifically addressing the evolving challenges in rapidly urbanizing regions like China. As urbanization accelerates, the quantity of urban parks has grown substantially, but challenges related to their design quality persist. This research bridges these gaps by integrating multidimensional insights across perceptual, emotional, and stress recovery dimensions into actionable recommendations, ultimately offering a integrative approach to urban park design and evaluation. This research introduces a robust methodology for LVQ assessment, combining spatial, visual, and physiological indicators with advanced technologies such as VR, eye-tracking, and facial emotion recognition. These methods enable precise pre-construction evaluations, minimizing resource wastage and ensuring alignment with user expectations. The iterative process of design refinement, as illustrated in Figure 6.1, allows for continuous improvement of design proposals, balancing visual aesthetics, and emotional resonance. Urban planners and designers can adopt this process to systematically assess and refine urban park designs, ensuring that they meet both aesthetic and experiential objectives. The framework's adaptability allows it to be applied to various spatial contexts, from green-dominated parks to urban squares.

The Table 6.1 consolidates findings across all dimensions, presenting a structured guide for landscape designers and urban planners. By linking specific LVQ indicators with practical design strategies, the table serves as an invaluable reference for translating research insights into real-world applications. This integration of evidence-based insights empowers stakeholders to design urban parks that align with user needs while fostering sustainable urban development.

Bridging user-centered design with data-driven insights, this study provides evidence-based recommendations for urban park design. Designers can use this approach to address contentious design elements, ensuring that decisions are grounded in empirical evidence and aligned with user needs. The integration of physiological and visual data provides foundation for discussions among stakeholders, facilitating consensus and enhancing design outcomes.

Table 6.1: Positive and negative effects of indicators across three dimensions

	Positive Effects	**Negative Effects**
	Perception Dimension	
Beauty	DTHerbPlants: Extended dwell time on herb plants reflects their visual appeal and aesthetic value, enhancing the perception of beauty. WaterRatio: A higher proportion of water enhances the scenic beauty through reflective and soothing visual properties. NumberOfElements: A greater diversity of elements increases visual richness, contributing to the perception of beauty. DegreeOfOpenness_Medium: Moderate openness (20–80%) balances spatial arrangement, creating visually pleasing compositions.	SkyRatio: Higher sky proportion reduces the density of greenery, negatively impacting perceived beauty. ArtificialObjects: Artificial elements such as benches or trash bins detract from the natural aesthetics, reducing perceived beauty.
Comfort	WaterRatio: The presence of water features promotes a sense of relaxation and comfort. CrownCoverage: Tree canopy coverage provides shade and reduces direct sunlight, enhancing physical and psychological comfort. NumberOfElements: Diverse elements create visually stimulating environments that feel comfortable.	RoadRatio: Roads often reduce vegetation density, leading to a less comfortable environment. PlantingStyle_Linear: Rigid and uniform linear planting lacks diversity, reducing relaxation and comfort.

	Positive Effects	**Negative Effects**
Color	WaterRatio: Water surfaces add blue hues to the environment, enhancing color diversity. FlowerRatio: The proportion of flowers increases visual vibrancy and aesthetic appeal. NumberOfMaterials: Greater material diversity enhances the richness of color perception. ContrastDegree_High: High contrast between elements highlights color differences, enriching the visual experience.	RCGrasses: Large uniform grasslands limit color diversity, reducing perceived vibrancy.
Complexity	RCHerbPlants: Herb plants with intricate patterns and colors contribute to visual complexity. WaterRatio: Reflections on water surfaces enhance the visual layering of a scene, increasing complexity. ShrubSpecies: Diverse shrub species add richness to vegetation patterns, enhancing complexity. NumberOfMaterials: Material diversity introduces visual variety, fostering complexity. PlantingStyle_Group: Grouped planting styles create layered vegetation patterns, enhancing complexity.	RoadRatio: Roads interrupt natural patterns, simplifying the visual composition and reducing complexity.

	Positive Effects	**Negative Effects**
Liveliness	DTHerbPlants: Herb plants with vibrant colors and diverse textures add dynamism to the landscape, fostering liveliness. WaterRatio: Flowing or reflective water surfaces introduce movement, enhancing liveliness.	ShrubSpecies: Dense or monotonous shrubs can obscure views, reducing the dynamic feel of the space. SpaceTypeCategories: Limited variety in space types diminishes visual stimulation, reducing liveliness. DegreeOfOpenness_High: Highly open spaces with sparse elements feel static, reducing perceived liveliness.
Greenness	ShrubSpecies: A diverse range of shrubs enriches vegetation and enhances greenness perception. DegreeOfOpenness_Low: Enclosed spaces surrounded by vegetation intensify the perception of greenery. PlantingStyle_Isolated: Isolated plantings draw visual focus, amplifying the perception of greenery.	DTShrubs: Monotonous shrubs limit vegetation diversity, reducing perceived greenness. RCArtificialObjects: Artificial elements distract from vegetation, lowering greenness perception. RoadRatio: High road coverage reduces vegetation density, negatively impacting greenness perception.
Safety	SpaceTypeCategories: A variety of space types with clear visibility improves safety by reducing hiding spots. DegreeOfOpenness_High: Open spaces with clear sightlines enhance safety perception. ContrastDegree_High: Brightly colored or contrasting features improve visibility, promoting safety.	DTTrees: Dense tree coverage obstructs visibility, reducing perceived safety.

	Positive Effects	**Negative Effects**
Emotion Dimension		
Valence	Herb Plants: Enhance emotional valence. Water Landscapes: Enhance emotional valence. Flowering Trees: Trigger positive physiological responses, such as relaxation.	Shrubs: Reduce emotional valence due to vision-limiting characteristics. Artificial Objects: Improper design or excessive proportions provoke negative emotional responses.
Arousal	Herb Plants: Enhance emotional arousal. Water Landscapes: Enhance emotional arousal. Grass: Quickly capture attention, fostering active interaction and a dynamic environment.	Flowering Trees: Longer fixation durations associated with calmer arousal levels. Shrubs: Reduce emotional arousal due to vision-limiting characteristics.
Emotion/Stress Recovery Dimension		
Calmness	Enhanced by higher sky proportion, promoting openness and flexibility.	Reduced by dense green-leaf trees and shrubs, which can create a sense of restriction and limit visibility.
Happiness	Increased by the presence of green-leaf trees and shrubs in balanced proportions.	Diminished by overly open spaces with a higher sky proportion.
Disgust	Minimized through balanced greenery (green-leaf trees and shrubs).	Triggered by overly dense greenery, particularly when tree density is high, creating a visually overwhelming setting.
Stress Recovery	Best supported in spaces like Zhongshan Square with thoughtful spatial arrangements and openness.	Impeded by imbalanced proportions of greenery and hardscape features.

6.2.3 Contribution to knowledge science

This dissertation advances the domain of knowledge science by providing integrative frameworks, empirical evidence, and methodological developments that enhance our understanding of the interplay between urban park landscapes and human perceptions. The integration of multidimensional visual indicators, physiological signals, and psychological responses bridges existing gaps in urban planning, environmental psychology, and landscape evaluation, creating new pathways for research and application.

1. Advancement of multidimensional assessment methods. This research introduces a novel approach to evaluating LVQ by combining eye-tracking, semantic image segmentation, and spatial feature indicators. Improved model differentiation of positive and negative perceptions by 1–7% using multidimensional visual indicators.
2. Providing evidence-based guidance for landscape design. This research delivers empirical evidence that supports the refinement of urban park design based on users' perceptual and emotional responses. By identifying landscape features—such as herbaceous plants, water elements, and spatial openness—that enhance perceived beauty, emotional well-being, and visual engagement, the study offers practical references for landscape architects and designers seeking to optimize the restorative and aesthetic functions of urban green spaces.
3. This interdisciplinary integration has brought new strategies and ways of thinking to knowledge development and organizational learning (Fig. 6.2). By bridging visual landscape, environmental psychology, and urban design, the proposed framework offers a novel perspective for understanding how multidimensional visual indicators interact with human perceptual, emotional, and stress recovery responses. The integration of diverse data sources—including eye-tracking, image segmentation, spatial features, and physiological and psychological measures—enables a deeper and more nuanced analysis of human–environment interactions. Such an approach not only advances methodological innovation but also promotes a more holistic, user-centered paradigm in the evaluation and design of urban park landscapes. Ultimately, this cross-disciplinary framework contributes to the evolving body of knowledge in urban landscape research and provides a foundation for evidence-based, emotionally supportive design strategies.

These contributions not only fill existing gaps in the literature but also propose new pathways for future research, particularly in the adaptation of emerging technologies to understand and enhance the human experience in urban landscapes.

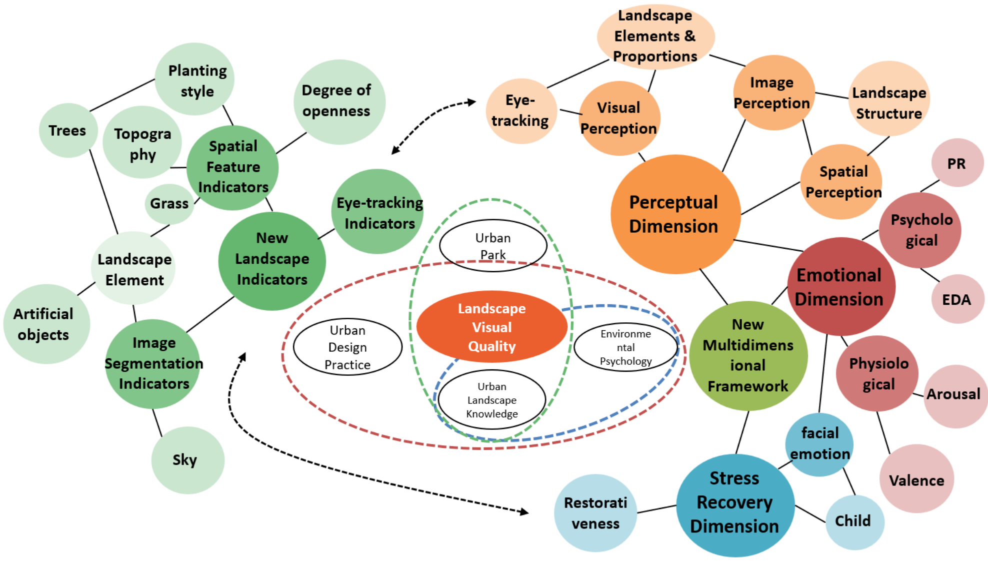


Figure 6.2: Multidimensional framework contributing to knowledge science in urban park landscape research.

6.3 Limitations and future works

This dissertation explores the multidimensional impacts of urban park landscapes on perception, visual behavior, emotion, and stress recovery. While the findings contribute valuable insights for urban design and environmental psychology, several limitations were identified across the three studies, highlighting directions for future research.

6.3.1 Study 1: Limitations in VR-based LVQ assessment

Although the use of VR-based panoramic imagery enabled controlled and immersive evaluations, the static visual content lacked the sensory richness and dynamic interaction of real-world environments [100, 197, 198]. Future studies are encouraged to integrate dynamic VR simulations or field experiments to enhance ecological validity and user immersion. The study's limited sample—comprising mostly young participants—and its focus on the summer season restrict the generalizability of the results. Given evidence of age-related differences in landscape preferences [199], future research is recommended to include participants across diverse age groups and consider seasonal variations to provide more comprehensive design guidance. Furthermore, only three parks were included, each with distinct designs. While this offered some variation, a broader sampling across multiple park types and regions is needed to improve representativeness. Applying audit tools to screen and classify urban parks systematically could support the development of region-specific design strategies [117]. Finally, although the proposed LVQ evaluation framework proved effective for perception classification, its application to larger and more diverse datasets remains to be tested. Future research is encouraged to validate this model in different contexts and explore its scalability for broader use in urban design decision-making.

6.3.2 Study 2: Emotional responses and visual behavior in VR

This study employed a multimodal approach—integrating psychological, physiological, and visual behavior data—to examine how specific landscape elements influence emotional responses and visual behavior. The use of controlled VR environments allowed for precise isolation of variables and supported scalable, repeatable evaluations of LVQ-related emotional effects. However, several limitations are worth noting. First, while VR offers experimental control, it lacks the multisensory and social dynamics of real-world environments. Emotional responses in actual parks are shaped by sounds, movement, and interactions that were not fully captured in the virtual setting. Second, the study focused on short-term visual exposure; longer-term emotional and behavioral effects remain unexplored. Future research could employ longitudinal or repeated-measures designs to investigate lasting impacts. Third, the findings are based on urban parks in China, limiting cross-cultural generalizability. Landscape preferences vary by culture, urban form, and climate; thus, replication in diverse settings is needed. Finally, this study centered on visual and physiological responses. Expanding to include auditory, olfactory, and tactile inputs would provide a more holistic understanding of how landscapes influence emotion and well-being. Despite these limitations, this study contributes a robust framework for evaluating emotional dimensions of LVQ. Its insights can inform the design of emotionally supportive, visually engaging urban green spaces that promote user well-being and enhance livability.

6.3.3 Study 3: Emotional and stress recovery responses in children

In the third study, we examined the relationship between LVQ and children's emotional responses, emphasizing the importance of spatial openness and balanced greenery in supporting stress recovery. However, the relatively small and age-homogeneous sample limited our ability to explore differences across gender and age. As noted by Cacioppo et al. [200], broader demographic representation is necessary to better understand variability in emotional and stress responses.

Additionally, this study used video-based stimuli to maintain experimental control and ensure consistency across different landscape settings. While this approach minimized external interference, it may lack the ecological validity and interactivity of real-world environments. Rather than simply replacing videos with field experiments, future studies are encouraged to conduct on-site experiments under controlled environmental conditions (e.g., consistent lighting, weather, and crowd levels). This will help balance experimental rigor with ecological realism and provide deeper insights into children's responses in real urban park contexts. Combining controlled and naturalistic methods will also help clarify how direct engagement—such as physical activity and social interaction—influences the restorative effects of LVQ for children [201, 202].

Across all three studies, this dissertation highlights the critical role of LVQ in shaping human psychological and physiological responses. The multidimensional approach introduced here—combining perceptual, emotional, and behavioral data—offers a comprehensive framework for future research. However, limitations such as the restricted sensory scope of VR, the geographic specificity of the study sites, and the sample demographic constraints point to opportunities for further refinement. Future research is encouraged to expand the scope of LVQ assessment to include diverse cultural, regional, and environmental contexts. Integrate multisensory data (e.g., auditory and olfactory elements) to better understand the holistic impacts of urban park landscapes. Investigate the temporal dynamics of LVQ by assessing how seasonal variations influence perceptions and experiences. Explore the long-term impacts of LVQ on different user groups, incorporating longitudinal studies to assess sustained effects on well-being. By addressing these limitations, future studies can deepen the understanding of LVQ and its role in creating restorative, inclusive, and sustainable urban environments. These advancements will strengthen the connection between research findings and practical applications, ensuring that urban parks are designed to meet the evolving needs of diverse populations.

Appendix A

30 experimental panoramas

Figure A.1: 30 experimental panoramas.

Appendix B

Computation of block scale code in semantic segmentation of images

```
import cv2
import numpy as np

image_path = 'D:\\segment_02\\P101.png'

img = cv2.imread(image_path)

if img is None:
    print("Failed to load image")
else:
    total_pixels = img.shape[0] * img.shape[1]
    print(f"Total pixels in the image: {total_pixels} pixels.\n")

    unique_colors = np.unique(img.reshape(-1, img.shape[2]), axis=0)

    for color in unique_colors:
        mask = cv2.inRange(img, color, color)

        area = cv2.countNonZero(mask)

        percentage = (area / total_pixels) * 100

        print(
            f"The area of the labeled region with color {color} is {
                area} pixels, which is {percentage:.2f}% of the image
                .")
```

Appendix C

Definitions and meanings of visual behavior indexes

Category	Abbreviation	Explanation	Meanings
Time to First Fixation	TTFF	The time taken from stimulus onset up to the first fixation into a particular AOI (area of interest)	It can provide information about how certain aspects of an element are prioritized in a photo. [203]
Dwell Time	DT	The total time the user's gaze stayed within the AOI.	It provides insights into the viewer's interest and engagement with the content within the AOI. [204]
Fixation Ratio	FR	The ratio of the amount of time the user spends in a particular AOI to the total amount of time spent in all AOIs.	It reflects the relative importance or complexity of these elements to the viewer. [205]
Revisit Count	RC	The number of times the user's gaze entered the AOI.	This metric counts how many times a viewer returns their gaze to a specific area, suggesting recurring interest or the need for additional cognitive processing, which shows the element's importance or attractiveness over time. [204]
First Fixation Duration	FFD	The duration of the initial gaze at the AOI.	Reflects visual initial processing. It is the early state of viewing. [55] The higher the FFD, the more complex the initial processing.
Average Fixation Duration	AFD	Mean of fixation duration on each AOI. (i.e., Gaze duration mean)	It reflects the depth of cognitive processing, suggesting that longer fixations may indicate more complex cognitive engagement or deeper processing of the visual content in that specific area. [85]

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