MODELLING SOUNDSCAPE IN OPEN SPACE

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Modelling Soundscape in Open Space

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Certificate of originality

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement had been made in the text.

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Abstract

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Open spaces are indispensable components of urban environments, playing a vital role in enhancing residents' quality of life and fostering social interaction. Among the various indicators for evaluating the quality of open spaces, soundscape quality is regarded as a critical dimension. systematically assessing the soundscape quality of open spaces is particularly beneficial, as it enables a more comprehensive understanding of the multisensory nature of soundscape evaluation and the complexities of multifunctional zoning in compact urban areas. Therefore, this study aims to identify the key factors influencing soundscape quality and establish an integrated framework to systematically explore how multisensory and multifunctional factors collectively contribute to soundscape evaluation in open spaces.

The development of the integrated framework began with the identification of the key factors influencing soundscape quality in urban open spaces. While prior research has consistently demonstrated the significant role of both objective physical attributes and subjective perceptions of auditory and visual factors in shaping soundscape evaluations, empirical investigations addressing the effects of micro-scale functional spaces and climatic factors (e.g., thermal conditions) remain insufficient. This research gap is particularly significant in compact cities located in hot regions, where thermal discomfort and spatial multifunctionality are common. To systematically examine their combined effects on soundscape quality, the study adopted a mixed-methods approach, incorporating questionnaire

surveys, on-site measurements, soundwalks, and sound mapping across various functional spaces and under diverse audiovisual and thermal conditions. Preliminary bivariate correlation analyses, together with qualitative evaluations derived from sound maps, not only confirmed the influence of auditory and visual factors on soundscape quality but also identified micro-functional space and thermal conditions as key factors.

Based on the initially identified key factors, this study developed a path model to systematically validate and examine the direct and indirect effects of multisensory and multifunctional factors on soundscape quality within the integrated framework. The results revealed significant interactions among auditory, visual, and thermal environmental factors. Notably, pleasantness, visual quality, and thermal acceptability were all found to exert significant and positive influences on soundscape evaluation. Perceived dominance of traffic noise not only directly decreased soundscape quality but also intensified thermal discomfort, thereby further decreased soundscape quality. Furthermore, children's play activities in playgrounds were found to markedly enhance soundscape pleasantness.

To deeply understand the influence of microscale functional spaces within the integrated framework, an ordered logistic regression model was also developed based on soundwalk investigations. The primary objective of this model was to examine whether different microscale functional spaces and their associated activities exert a significant influence on soundscape evaluations, and to assess their relative importance in comparison with widely acknowledged auditory and visual factors. The analysis demonstrated that microscale functional spaces play a significant role in shaping soundscape quality, although their relative impact was found to be weaker than that of auditory and visual factors, with an approximate relative influence ratio of 1:3. In addition, the model confirmed the path model finding that children's play activities in playgrounds significantly enhance the vibrancy and pleasantness of the soundscape. It also deepened the understanding of how micro-functional spaces influence soundscape perception, showing that mechanical noise in sitting-out areas significantly reduces soundscape quality, whereas natural sounds such as rustling leaves contribute positively in these contexts.

Although the path model and the ordered logistic regression effectively revealed the causal relationships and relative importance, their analyses were primarily based on linear assumptions. This limited their capacity to capture nonlinear variations arising from sensory thresholds and complex cross-modal interactions. To address these limitations and further enhance the practical applicability of the integrated framework, this study employed explainable machine learning techniques. Specifically, an Extreme Gradient Boosting (*XGBoost*) algorithm combined with SHapley Additive exPlanations (SHAP) analysis was used to develop a more flexible and interpretable prediction model. The results revealed that A-weighted equivalent continuous sound level *(LAeq)*, perceived road traffic noise, greenery percentage, and Physiological Equivalent Temperature (*PET*) are the key factors of predicting soundscape quality. Moreover, the analysis revealed significant nonlinear interaction effects, particularly between sound and thermal conditions, which had a significant impact on soundscape evaluation. The successfully constructed machine learning model validated the effectiveness of the integrated framework and provided deep understanding of the impact of key factors on soundscape.

This study's unique contribution lies in the development of a comprehensive framework for understanding how multisensory and multifunctional factors jointly influence the soundscape quality of open spaces. By integrating auditory, visual, and thermal factors with micro-functional space types, this framework not only advances the theoretical understanding of soundscapes but also provides practical tools for urban planners and designers to create high-quality soundscapes and open space.

Publications arising from the thesis

Journal papers:

Lin, M. Q., Chau, C. K., Tang, S. K., Chung, W. K., Yu, H. M., (2025), Determinants of soundscape quality of communal open space in Hong Kong, Building and Environment, 267, 112261.

Lin, M. Q., Chau, C. K., Hou, H. Y., Tang, S. K. (2025). Development of an interpretable machine-learning model for capturing nonlinear dynamics of multisensory interactions in public open spaces. Building and Environment, 113072.

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Table of Contents

List of Tables

List of Figures

Chapter 1 Introduction

1.1 Research background

With the rapid development urbanization, outdoor open spaces serve as significant components of high-density cities. These spaces not only accommodate multiple functions (e.g., rest, social interaction, pedestrian circulation, and ecological buffering), but also play a vital role in enhancing residents' quality of life, fostering community cohesion, and mitigating urban heat. Consequently, improving the environmental experience of open spaces has become a central concern in both urban design and public health research (Lin et al., 2025). While conventional enhancement strategies have primarily focused on physical attributes (i.e., greening, spatial configuration, and aesthetic design) (Aletta et al., 2016b), growing attention has been paid to soundscape as a perceptual and human-centered dimension (Erfanian et al., 2019). Soundscape was defined as "an acoustic environment as perceived or experienced by people, in context." In high-density urban settings, where open spaces often play multifunctional roles within complex sensory environments, the experience of soundscapes is shaped not only by the auditory environment but also by the functional context, ongoing activities, and multisensory inputs. Indeed, the same sound may evoke distinct responses depending on the spatial setting and surrounding stimuli. Within this context, enhancing soundscape quality in high-density urban open spaces requires a deep and comprehensive understanding of two dimensions. On one hand, soundscape perception is inherently multisensory, shaped not only by auditory input but also by visual and thermal stimuli, as well as their complex interactions. On the other hand, the multifunctionality of open spaces introduces significant contextual variability—different spatial functions and the dynamic nature of ongoing activities fundamentally alter how soundscapes are perceived and evaluated. To address these challenges, this study proposes the development of an integrated analytical framework that systematically incorporates multisensory inputs and functional spatial attributes to uncover the key mechanisms influencing soundscape quality in urban open spaces and provide evidence-based strategies for their enhancement.

Building on the understanding that soundscapes are context-dependent and multisensory in nature, recent research has increasingly focused on how various sensory inputs (particularly auditory (Kang and Schulte-Fortkamp, 2016; Pijanowski, 2011), visual (Jeon et al., 2011), and thermal perceptions (Lin et al., 2025; Mohammadzadeh et al., 2023) interact to shape soundscape evaluations in urban open spaces. Natural auditory cues, such as birdsong, are widely recognized for enhancing soundscape (Zhao et al., 2020), while artificial noises like road traffic are frequently associated with annoyance and psychological stress (Kogan et al., 2018). Visual features, such as greenery or urban infrastructure, further modulate these effects by enhancing or decreasing auditory impressions. For example, greenery has been found to enhance the perceived pleasantness of natural sounds, whereas visible roadways can amplify the negative perception of traffic noise (Liu et al., 2014a). Moreover, the contextual appropriateness between what is seen and heard plays a critical role in shaping soundscape quality. Despite these advances, the role of thermal perception, such as heat stress and thermal discomfort, remains unclear. Although some studies have reported correlations between thermal, visual and auditory comfort, the mechanisms underlying these cross-modal interactions remain largely unexplored. As a result, this limitation reduces the ability to assess how multisensory inputs collectively shape soundscape experiences in complex urban environments.

Beyond the influence of multisensory environmental stimuli, the functional use of space and the presence of ongoing activities also play a critical role in shaping soundscape perception (Hong and Jeon, 2015, 2017b). Variations in activity types can lead to significant differences in how individuals evaluate soundscapes (Bild et al., 2018). Leisure activities such as walking or sitting in a park may enhance the appreciation of natural sounds (Aletta et al., 2016a), while high-intensity activities or large crowds could increase the perception of noise (Jeon and Hong, 2015). The frequency and intensity of activities are closely tied to the dynamic changes in soundscapes, as certain activities amplify or mitigate specific sound sources (Liu et al., 2013b; Pijanowski, 2011). As urban space becomes increasingly constrained, open spaces are expected to serve multifunctional roles, accommodating a diverse range of recreational, social, and utilitarian activities. However, research remains limited in examining how these activities within different functional zones interact with the surrounding environmental context. A comprehensive understanding of these dynamic relationships is essential for guiding the design of open spaces that effectively balance diverse user needs while optimizing soundscape quality.

To better capture the complex relationships among key factors and soundscape evaluations, researchers have developed prediction models (Lionello et al., 2020). Traditional models often emphasize physical factors, such as sound pressure levels (e.g., LAeq) (Pheasant et al., 2008; Ricciardi et al., 2015; Romero et al., 2016) and greenery percentage (Pheasant et al., 2008), or subjective perception factors, such as the visibility of the sky (Liu et al., 2014a; Wang et al., 2022) or the perception of birdsong (Wang et al., 2022). While these models have contributed valuable insights, they often fail to account for the complex interactions between key factors. Moreover, their reliance on linear assumptions limits their ability to capture the dynamic and nonlinear relationships that characterize soundscape evaluations. Emerging advancement in modeling techniques highlight the necessity of incorporating climatic variables, such as thermal environments, alongside multisensory inputs (Jin et al., 2020; Lau and Choi, 2021; Nitidara et al., 2022). The adoption of more integrative frameworks can enhance the accuracy and interpretability of soundscape assessments, ultimately providing more effective guidance for urban planners and designers in optimizing open space environments.

1.2 Research objectives

All in all, soundscape research has made significant progress in understanding how auditory and visual factors influence soundscape evaluation. However, there remain critical research gaps in comprehensively addressing the complex and interrelated impacts of multisensory interactions and ongoing activities within functional areas on soundscapes, particularly in the context of high-density urban open spaces. By proposing a more comprehensive framework, researchers can develop more effective strategies to optimize urban soundscapes, ensuring they meet both functional demands in rapidly urbanizing contexts and the overall enhancement of soundscape quality. Specifically, the major objectives of this study are:

- To identify the determinants influencing soundscape experience in multifunctional open spaces in high-dense cities;
- To propose a comprehensive soundscape evaluation framework and explore the intricate interrelationships among these determinants;
- Based on the proposed framework, assessing and quantifying the significance of micro-scale functional space types and associated activities in achieving high-quality soundscapes;
- To develop an advanced modelling approach based on the proposed framework for soundscape to capture and quantify the multisensory interactions;
- To apply the developed model to propose targeted measures aimed at improving the soundscape quality of multifunctional open spaces in high-dense cities.

1.3 Significance of the findings

This study proposed a comprehensive multidimensional framework to support the enhancement of soundscapes in compact urban open spaces, particularly within high-density city contexts. From a multisensory perspective, the framework integrates auditory, visual, and thermal dimensions, emphasizing their interactive effects on soundscape perception. This allows for a more holistic understanding of how perceptual inputs from different modalities collectively shape the soundscape experience. On the functional dimension, the study systematically evaluates the role of functional spaces and their associated activities, quantifying their specific impacts and identifying activity types that align most effectively with spatial intent. In addition, advanced machine learning models are employed to elaborate complex feature interactions and threshold effects, significantly improving the accuracy and interpretability of soundscape prediction. These findings offer both theoretical contributions and practical tools for optimizing open space soundscapes in rapidly urbanizing, high-density environments.

1.4 Thesis structure

This thesis is organized into eight chapters, each addressing different aspects of soundscape evaluation in outdoor open spaces in compact city and aiming to create a systematic framework for understanding and predicting soundscape quality. A detailed outline of each chapter is as follows (See Figure 1-1):

Chapter 1 introduces the background, objectives along with structure of the thesis.

Chapter 2 includes a comprehensive review of literature related to soundscapes, landscape characteristics, cross-modal perception, and prediction models, establishing the theoretical foundation and analytical framework for the study.

Chapter 3 describes the methods of data collection, including questionnaire surveys, on-site measurements, soundwalks, and sound maps, ensuring reliable data support for subsequent analysis.

Chapter 4 explores the determinants influencing soundscape evaluation through simple correlation analysis and qualitative analysis of sound maps, laying the groundwork for subsequent model development.

Chapter 5 employs structural equation modelling (SEM) to systematically reveal the complex relationships among soundscape determinants, providing theoretical framework support from a holistic perspective.

Chapter 6 analyzes the specific impacts of landscape contextual factors (e.g., micro-scale functional space types) on soundscape evaluation.

Chapter 7 utilizes machine learning models to examine the nonlinear relationships between soundscape evaluation and key determinants, while also uncovering the interactions among different factors.

Chapter 8 summarizes main findings, discusses practical implications, and suggests directions for future research.

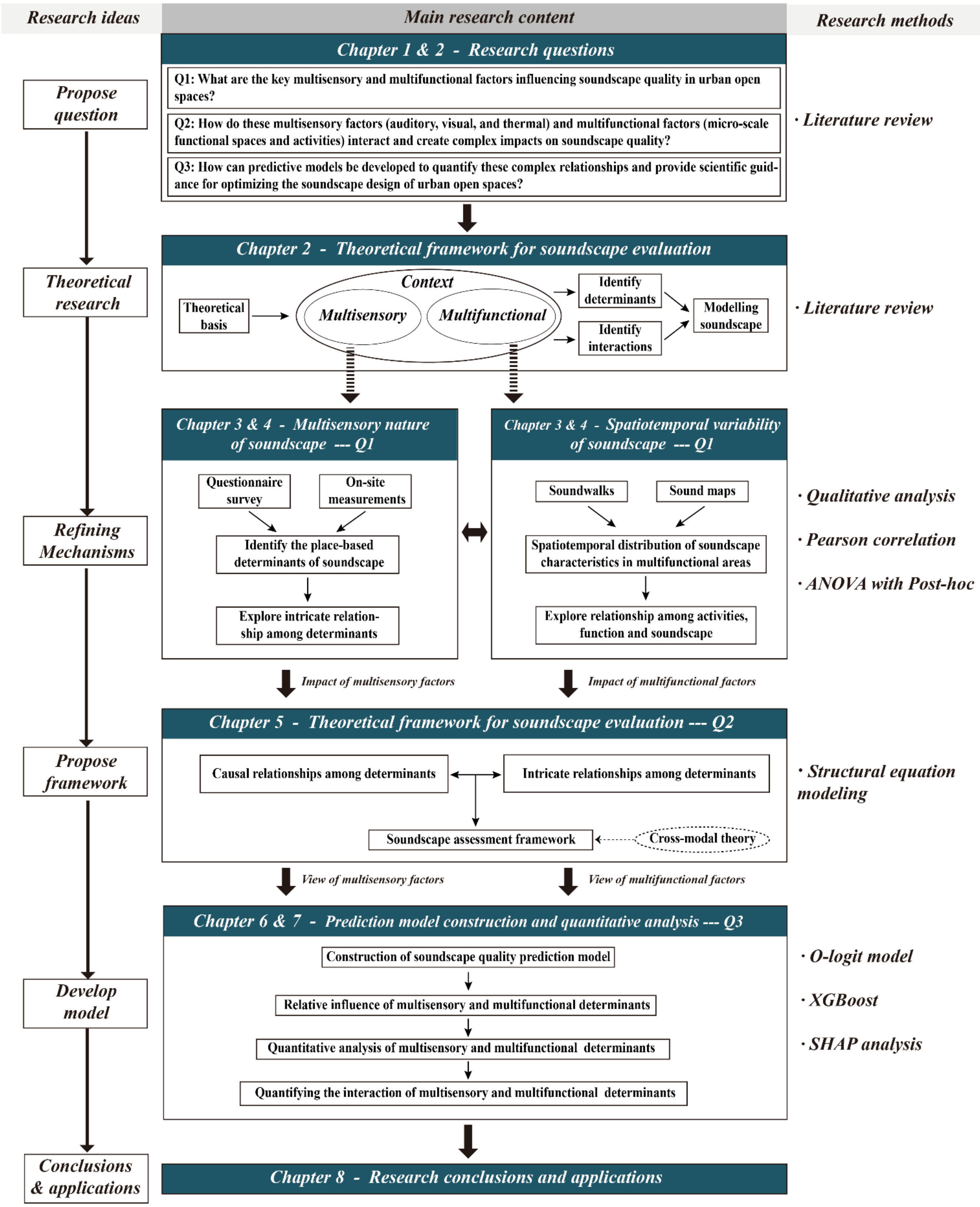


Figure 1-1 The technical roadmap of the thesis

Chapter 2 Literature review

This literature review begins by outlining the conceptual foundation of soundscape, emphasizing its definition as the acoustic environment as perceived by people in context. Soundscape quality is increasingly recognized as a vital dimension of the overall environmental experience in urban open spaces, especially in compact cities where environmental complexity and functional density are pronounced. To better understand what shapes soundscape perception, this chapter systematically reviews some critical dimensions: multisensory factors, which include auditory, visual, and thermal components and their interactions, and multifunctional spatial factors, particularly the influence of micro-scale functional spaces and ongoing activities. Special attention is given to how these dimensions interact to affect perception, going beyond isolated factor analysis. Moreover, the review identifies significant research gaps—while previous studies have often focused on macro- and meso-level environmental or functional attributes, insufficient attention has been paid to the nuanced roles of micro-functional spatial contexts in shaping soundscape experience in high-density urban settings. Finally, this chapter evaluates existing predictive approaches (e.g., linear regression and machine learning) and discusses their limitations in capturing nonlinear relationships and multisensory interactions, highlighting the importance of incorporating threshold effects and complex interactions in future soundscape research.

2.1 Foundations and emerging directions in soundscape

The concept of soundscape was first introduced by Schafer in 1977 and later formalized by the International Organization for Standardization (ISO 12913-1) in 2014 as "an acoustic environment as perceived, experienced, and/or understood by a person or group of people, in context". This definition emphasizes three core aspects: subjectivity (the variability of individual perception), contextuality (the dependence of acoustic experiences on spatial and temporal contexts), and multidimensionality (the interaction between auditory and other sensory inputs). This paradigm shift extends the scope of acoustic environment studies beyond traditional physical acoustics, incorporating psychological, social, and contextual attributes, thereby providing a theoretical foundation for scientifically evaluating and optimizing sound environments.

Compared to traditional noise management, soundscape research offers significant theoretical and practical innovations. Conventional noise management focuses primarily on physical noise reduction, relying on metrics such as sound pressure level (*SPL*) and employing technical solutions like noise barriers and source control to mitigate the adverse effects of noise (Kuo and Morgan, 1999). However, this approach overlooks the holistic nature of sound and the contextualized perception of individuals. Soundscape research, in contrast, adopts a resource-based perspective, recognizing sound as a valuable environmental asset rather than a mere pollutant (Schafer, 1993). For instance, natural sounds such as birdsong and water sounds can enhance psychological well-being and promote restorative experiences—benefits that conventional noise control measures fail to address (Hong et al., 2020b). This perspective further emphasizes the concept of appropriateness (Jo and Jeon, 2020a; Yang et al., 2024), which evaluates whether sounds align with their spatial and activity contexts, offering a more comprehensive strategy for optimizing acoustic environments in open spaces.

To scientifically evaluate soundscapes, researchers have identified a range of key dependent variables, or descriptors, that characterize soundscape quality (Aletta et al., 2016b). These descriptors include perceptual affective quality (Axelsson et al., 2010; Lin et al., 2025), restorativeness (Payne, 2013), overall perceived quality (Axelsson, 2015; Lin et al., 2025), and appropriateness (Jo and Jeon, 2020a; Yang et al., 2024). Perceptual/affective quality captures the emotional responses elicited by the acoustic environment, often measured through dimensions such as pleasantness and eventfulness. Restorativeness highlights the potential of soundscapes to alleviate stress and restore attention, particularly in natural settings. Overall perceived quality reflects a holistic subjective assessment of the acoustic environment, integrating various sensory inputs. Appropriateness examines whether the sounds are contextually aligned with their environment or associated activities, representing a core dimension of contextualized soundscape research. Studies have shown significant relationships among these descriptors. For example, overall soundscape quality is highly correlated with perceptual/affective quality, suggesting that the latter serves as a strong predictor of the former. Theoretically, restorativeness should also correlate positively with low eventfulness and high pleasantness, although this relationship remains underexplored (Aletta et al., 2016b). These findings indicate that most descriptors converge on the affective two-dimensional model of soundscape perception, underscoring their interconnected nature.

Predictors influencing these soundscape descriptors can be categorized into four dimensions: physical acoustic features (Lin et al., 2025; Rychtáriková and Vermeir, 2013), environmental attributes (Jeon and Hong, 2015; Lin et al., 2025; Rychtáriková and Vermeir, 2013), personal characteristics (Chan et al., 2023; Jeon et al., 2021), and activity contexts (Bild et al., 2018). Physical acoustic features, such as sound pressure level (Sudarsono et al., 2016), frequency distribution (Pijanowski et al., 2011), and temporal characteristics (Botteldooren et al., 2006), provide the fundamental data of the acoustic environment. Environmental attributes include visual elements (e.g., greenery coverage, building density) (Lin et al., 2025; Liu et al., 2019) and microclimatic factors (e.g., temperature, humidity) (Lin et al., 2025; Mohammadzadeh et al., 2023). Personal characteristics encompass demographic factors (e.g., age, gender), cultural background, and auditory preferences, which determine subjective responses to soundscapes. Activity contexts, including activity type, density, and spatiotemporal variation, directly shape users' psychological expectations of the acoustic environment. Moreover, understanding the intrinsic relationships among predictors is critical.

For example, interactions between visual landscapes and auditory perceptions may influence evaluations of overall soundscape quality, while activity density could modulate dynamic environmental changes, further affecting perceptual quality. These complex interrelationships highlight the multifaceted and non-linear nature of soundscape perception, necessitating a systematic approach to comprehensively unravel these mechanisms.

Given the multidimensional nature of soundscape perception, an increasing number of research has focused on building integrative theoretical framework that can systematically account for both sensory inputs and contextual influences. In particular, the interactions among auditory, visual, and thermal stimuli as well as their contextual modulation by spatial functions and ongoing activities presents a critical area for exploration. While several conceptual frameworks have emerged to address these complexities, many remain either limited in scope or overly reliant on categorical factor separation (e.g., personal vs. environmental). To move beyond these constraints, there is a pressing need to establish a more holistic and empirically grounded framework that synthesizes multisensory integration and multifunctional spatial usage as core mechanisms driving soundscape quality.

This study aims to advance the theoretical understanding of soundscape perception by proposing a comprehensive framework that integrates multisensory and multifunctional factors. Rather than treating these dimensions as isolated variables, the framework emphasizes their dynamic interactions. Moreover, the study empirically investigates how these interactions affect subjective perception in micro-scale functional spaces within high-density urban open environments—settings that are often overlooked in previous studies. By combining theoretical hypothesis with empirical validation, this research aims to generate actionable insights for optimizing soundscapes in complex urban settings, offering both academic contributions and practical implications for evidence-based planning and design.

2.2 Multisensory perspective on soundscape

The soundscape quality of open spaces is significantly shaped by sensory factors, which serve as critical determinants in the evaluation of auditory environments. These factors are broadly categorized into three main domains: sound characteristics, landscape attributes, and microclimatic conditions. Together, these elements create a multisensory context that influences the perception and evaluation of soundscapes. The interplay between these factors not only defines the physical attributes of the space but also shapes the subjective experiences of individuals. Importantly, the impact of these elements on soundscape quality often operates through multisensory interactions, highlighting the need for a holistic approach to understanding the impact of place-related factors.

Soundscape quality of open space is influenced by type of sound sources present, as well as the basic physical properties of its sound sources like sound pressure level (Irvine et al., 2009; Ricciardi et al., 2015) and frequency (Hong et al., 2021), and dynamic patterns like temporal profile and intermittency (Jeon et al., 2010). Given that open spaces often entail cocktails of different types of sounds, their composition and variations are also determinants for soundscape quality (Tse et al., 2012). In addition, type of open space e.g., parks (Tse et al., 2012) and squares (Jin et al., 2020), is also an important determinant since different types and characteristics of sounds are emanated from different functional landscapes (Hong and Jeon, 2017b).

In evaluating the soundscape of open spaces, it is crucial to recognize that beyond the objective physical sound properties, human perception significantly influences soundscape assessment as soundscape is a perceptual construct of a sound environment (Axelsson et al., 2010; Jeon and Jo, 2020; Kang et al., 2016). Therefore, we must clearly distinguish this perceptual construct from the tangible physical surroundings.

Conceivably, human perceptions of sounds play an important role in soundscape assessment. Preference and perception of specific types of sounds by open space users have been shown to affect their soundscape assessment of an open space. Positive sound assessments will be evoked for perception of favorable sounds while negative assessments will be evoked for perception of unfavorable sounds. People generally prefer to hear natural sounds, e.g., water sounds (Jeon et al., 2012; Lugten et al., 2018) or birdsong (Jo and Jeon, 2020a, b), but dislike mechanical sounds like vehicle noise (Jeon and Hong, 2015; Jeon et al., 2010) and human sounds (Tse et al., 2012). However, even for same types of sound sources, different frequency spectra or temporal variation will evoke different soundscape assessments. For instance, high pitch birdsong was more preferred to low frequency one (Chau et al., 2023) and high sharpness water sound with less temporal variation was less preferred (Galbrun and Ali, 2013). Besides, the dominancy of sound sources perceived by users was also found as a determinant of soundscape quality in open space (Pérez-Martínez et al., 2018). A higher soundscape quality rating would be received if the most dominant sound type shifted from artificial to natural (Chau et al., 2023; Ren, 2023). Thus, further exploration is required to determine whether specific types of sounds must be perceived as dominant by open space users or if their mere presence is sufficient to influence soundscape quality assessment.

As human perception is multi-sensory in nature, the cross-modal interactions between aural and other types of sensory perceptions, such as visual-aural interactions, have been determined to affect soundscape assessment in open space. Visual landscape of open space has been determined to affect its soundscape assessment through visibility of specific natural and built landscape features. Generally, views of natural features, e.g., greenery (Jo and Jeon, 2020a; Lugten et al., 2018) and water (Lugten et al., 2018), will help to produce positive soundscape assessments. On the contrary, views of some artificial features will produce negative soundscape assessments. Visibility of roads produced negative effects on soundscape assessment (Jeon et al., 2010). However, the effect of visibility of densely packed buildings on soundscape assessment is less ascertained as they were found likely to produce negative soundscape assessment in a street environment in Seoul (Hong and Jeon, 2013), but not in a high-rise residential area in Singapore (Tan et al., 2022).

In comparison, the interaction effects between thermal and aural perceptions have been less comprehensively investigated in outdoor open space, despite majority of earlier studies having only focused on exploring their bivariate correlation relationships. People were found more sensitive to the perception of noise in hot environments (Yin et al., 2022). Hotter thermal condition tended to produce lower sound quality (Lau and Choi, 2021). Conversely, thermal perceptions can also be modified by sound characteristics. Different sound types would influence thermal comfort differently (Chen et al., 2022; Geng et al., 2022). Perception of music and natural sounds was found positively correlated with thermal comfort in a campus open space in a cold climate region (Chen et al., 2022; Geng et al., 2022). The extent of improvement was found to vary with type of sounds (Chen et al., 2022) and season (Geng et al., 2022). Conversely, perception of unwanted sounds like people crowd noise and machine noise would decrease thermal comfort (Geng et al., 2022). Besides, high sound pressure level significantly deteriorated thermal comfort in summer (Jin et al., 2020). Loud/noisy sound sensation increased the thermal sensation in parks and squares in a tropical climate city (Nitidara et al., 2022), and high traffic noise level slightly increased the thermal sensation in squares during summer in a cold climate country (Jin et al., 2020). On the contrary, low sound level would produce a more comfortable acoustic environment, leading to enhanced thermal comfort (Chen et al., 2022).

Above all, there is still a number of research gaps that have not been fully addressed. First, majority of findings have been focused on exploring the effects of single aspects of multisensory factors on soundscape quality. In addition, most of them reported only on the bivariate relationships between soundscape quality and influencing factors in terms of correlations instead of causation, which makes it impossible to conclude which factor causes change in the other. Second, there is a lack of understandings on the relative influences and direction of effects of various types of sound sources on thermal perception and vice versa despite majority of earlier efforts being mainly focused on revealing the bivariate relationships between thermal environment and perceptions, and acoustic comfort, and/or their interactions. Third, majority of studies have been reported in a piecemeal manner, or focused only on one perceptual dimension of soundscape quality whose effects may not be fully applicable to the overall soundscape quality. Above all, there is a lack of studies that can holistically reveal whether and how the multisensory perceptual and physical micro-environment attributes influence soundscape quality in communal open spaces (COS) in residential housing estates in a high-dense or compact city, which are affected by rich arrays of road traffic and human sounds and built environment features.

2.3 Multifunctional perspective on soundscape

In cities where land resources are scarce, there is an urgent need for multifunctional open spaces that can meet the diverse needs of individual city inhabitants. Landscape design plays a significant role when designing these spaces to foster sustainable and healthy urban environments (Jackson, 2003; Ribeiro et al., 2023). Landscape design encompasses designing and planning of visible features such as vegetation, amenities, and landforms, ensuring they harmoniously integrate with natural or man-made features to achieve high aesthetic appeal. Beyond visual aspects, soundscape, an auditory counterpart to landscape - also influences people’s preference for open spaces (Liu et al., 2014a; Pijanowski, 2011). Pleasant soundscape can attract more visitors and encourage them to stay (Jo and Jeon, 2020a), while poor soundscapes may discourage people from visiting and lingering (Filipan et al., 2017), particularly in densely populated urban areas with heavy pedestrian and road traffic.

Soundscape is defined as the sound environment as perceived by people within a specific context. Consequently, the characteristics of sound environment including sound pressure level (Hong and Jeon, 2020; Hong et al., 2021; Yang and Kang, 2013), frequency, psychoacoustic parameters (Yang and Kang, 2013), and sound source type (Hong and Jeon, 2020; Yang and Kang, 2013) as well as individual perceptions of sound sources influence how an individual assesses the soundscape of open spaces. Considerable progress has been made in understanding how the physical acoustic environment and its human perception impact soundscapes, with relatively consistent findings. Generally, the perceptions of the presence and dominance of artificial or mechanical sounds (Kogan et al., 2018) tend to reduce the quality of open space soundscapes (Ma et al., 2021). Conversely, the perceptions of the presence and dominance of natural sounds tend to enhance soundscape quality (Hermida and Pavón, 2019; Ma et al., 2021). Similar to auditory perception, visual perceptions of natural features often enhance the open space quality while visual perceptions of some artificial features can degrade it.

Moreover, the impacts of context on soundscape evaluation are crucial and should not be underestimated, as it significantly affects how soundscapes are experienced and evaluated. Context encompasses the specific setting or environment in which sounds are heard and perceived, including physical, social, and cultural dimensions that shape the interpretation and experience of sounds. Contextual factors include temporal (Liu et al., 2013b; Zhao et al., 2022) and spatial aspects (Liu et al., 2014b; Liu et al., 2013b; Zhao et al., 2022), and activities (Kou et al., 2021). Evaluations of the acoustic environment, both subjective and objective, vary with seasons of the year (Bian et al., 2022) and time of day (Hong and Jeon, 2017b). Spatial characteristics influence the diversity of sound sources and acoustic environments, thereby affecting soundscape evaluations. Different types of neighborhoods (e.g., residential and commercial (Liu et al., 2013b)) and open spaces (e.g., streets (Liu et al., 2013b), parks (Liu et al., 2013b; Nilsson and Berglund, 2006), and green spaces (Liu et al., 2013b) often exhibit notable differences in soundscape quality. Spatial arrangement of natural and built features within open spaces affects visual openness, which can be defined as the degree to which a space allows unobstructed views and a sense of openness, without significant visual barriers. Visual openness influences both physical sound reflections and psychological stress, thereby altering soundscape assessments (Chung et al., 2022; Jeon et al., 2011). In addition, activities within a functional space can also significantly impact soundscape evaluation. For instance, adult activities in a rest area may lower the overall soundscape evaluation, whereas children's activities in a play area may enhance the liveliness of the soundscape (Lin et al., 2025).

A number of studies have delved into the contextual influences, primarily focusing on specific functional space type such as open space. Early research primarily concentrated on the macro-level urban scale, utilizing Geographic Information System (GIS) techniques to develop large-scale urban soundscape maps and spatial indicators to analyze variation trends across different open areas. For instance, Liu et al. (2013b) explored the spatiotemporal variations of soundscapes in multifunctional urban areas and found that soundscape composition is closely related to the underlying landscape characteristics of functional spaces. They suggested identifying differences in spatial landscape pattern indices across functional spaces and analyzing their relationships with soundscape components. For example, in garden areas with high normalized difference vegetation index (NDVI), biophonic sounds (e.g., bird songs) are more easily perceived, whereas in areas with high building density (CD) and road density (RD), vehicle noise becomes the dominant sound source. Furthermore, Hong and Jeon employed global and local spatial regression analyses to validate the spatial autocorrelation of soundscape quality at the macro-level. Zhao et al. (2022) utilized semantic segmentation with computer vision techniques to identify urban functional variables on a large scale and found that different levels of functional spaces (e.g., neighborhood scenes) significantly influence soundscape evaluations, including sound source perception and soundscape quality. Further, researchers have increasing interest on the meso-level, examining soundscape characteristics within specific categories of functional spaces. For example, Hong and Jeon (2017) investigated the relationships between sound source types, visual quality, and soundscape evaluations in commercial, residential, business, and recreational spaces, demonstrating that functional space types significantly influence soundscape perception. Xu et al. (2021) further revealed the contrasting relationships between sound levels and acoustic comfort in compact cities: in communication areas, sound levels are positively correlated with acoustic comfort, whereas in restoration areas, the two are negatively correlated.

While functional space types like neighborhood and open space have been studied, the effects of microscale functional space types within open spaces, like play areas and sitting-out areas, on soundscape quality has not been extensively explored. These specific types have yet to be compared or integrated into prediction models to quantify their varying impacts. Additionally, most of the existing models fail to adequately account for other contextual factors like time of day (Hong and Jeon, 2017a, b), activities (Kou et al., 2021; Pijanowski et al., 2011), and visual openness (Jeon et al., 2013), which influence people's soundscape evaluation, and can lead to prediction bias. Furthermore, these models were mostly derived from functional areas in low- to medium-density cities, which may not be suitable for multifunctional open spaces often found in high-density urban areas.

The close proximity of architectural and natural features in high-dense cities often significantly reduces visual openness for observers. When considering visual openness (Jeon et al., 2013; Lee et al., 2014), it is crucial to consider not only sky view, measured through subjective Likert scales or objective percentage of sky view (Jeon et al., 2013; Ren et al., 2018), but also the unobstructed open space near the observer. Early evidence suggests that, in addition to the commonly emphasized percentage of sky view, nearby objects can substantially impact the perception of openness (Abd-Alhamid et al., 2020; Abd-Alhamid et al., 2023). Close-up views, even those with pleasant vegetation, may evoke feelings of oppression and fear (Chung et al., 2019; Chung et al., 2022), ultimately negatively impacting soundscape perception. In addition, high-dense cities experience intense human and vehicle sound sources, whose impacts differ greatly from those in low- or medium-dense cities.

It remains unclear whether microscale functional space type, e.g., sitting-out and children play areas, exerts influences on soundscape quality evaluation of an open space within a residential housing estate in a high-dense city. Open spaces within residential housing estates are the major focuses of this study as they can facilitate social connections and foster a feeling of community among housing residents by offering valuable extra space in cramped dwelling space for majority of people in dense city areas. In this study, Hong Kong was selected as a representative high-density city. A key objective is to examine how specific activities within microscale functional spaces influence soundscape quality. For instance, the study investigates whether children's play in playgrounds enhances soundscape perception and whether similar effects arise from other activities in different spaces. In addition, the role of visual openness, shaped by the arrangement of natural and built features, is assessed. By comparing these contextual factors with more commonly recognized auditory and visual attributes, the study aims to clarify their relative contributions. These insights provide practical guidance for urban planners, particularly in prioritizing design strategies under resource constraints.

2.4 Understand the nonlinear effects of various factors on the soundscape

To create a good soundscape in an urban open space, it is essential to first understand people's perceptual preferences of acoustic environment, making accurate evaluation or prediction of soundscape assessment particularly important (Lionello et al., 2020). This perceptual process is not determined by a single sensory input but is influenced by the interplay of multiple sensory modalities. According to environmental psychology (Craik, 1973), environmental perception arises from multisensory integration, where human experiences are shaped by both collaboration and compensation mechanisms among various sensory inputs. Collaborative mechanisms, as described by the Holistic Perception Theory, integrate various sensory inputs into a unified perceptual experience (Genuit and Fiebig, 2006; Stein and Meredith, 1993). In contrast, compensatory mechanisms, as explained by the Sensory Compensation Theory, enhance overall perception when one sensory input is insufficient (Backman and Dixon, 1992; Groth et al., 2024). Existing multi-domain research has extensively examined how auditory, visual, and thermal factors jointly influence human perception, particularly in indoor environments. These studies emphasize that sensory stimuli do not function in isolation but rather interact in complex ways, leading to combined or cross-modal effects. While prior research primarily focuses on indoor settings, this study extends the multi-domain framework to urban open spaces, where environmental conditions are more dynamic. Unlike controlled indoor settings, urban spaces feature fluctuating noise levels, variable thermal conditions, and diverse visual landscapes, making the integration of multisensory factors even more complex. Thus, soundscape assessment, as a multisensory integration, exemplifies this complexity (Lin et al., 2025). For instance, greenery or water features, can not only alleviate visual fatigue but also shift attention away from negative sounds like traffic noise, thereby enhancing overall soundscape perception (Van Renterghem, 2019). Moreover, the effects of multisensory perception are significantly influenced by sensory thresholds (Stevenson et al., 2014). When sensory stimuli exceed or fall below certain critical levels, they may trigger nonlinear responses, thereby markedly altering individuals' overall evaluation of the environment. These lay the foundation for multisensory soundscape research, yet a comprehensive understanding is still lacking to explain the threshold effects and how multisensory information collaborates or competes to influence soundscape assessment.

In response to the absence of theoretical foundation model developments, researchers are considering the adoption of data-driven methodologies. Initially, deterministic approach utilizing linear regression methods has been employed to predict soundscape evaluation based on physical sound properties and/or psychoacoustic parameters. Ricciardi (Ricciardi et al., 2015) created a linear regression model by LA_{50} and LA_{10}-LA_{90} to predict soundscape quality with a low coefficient of determination (R^2) value of 0.21. Aydın (Derya ÇAKIR AYDIN, 2016) developed a sound quality index for urban spaces by incorporating psychoacoustic parameters including loudness, sharpness and roughness values. Although this model achieved a high R^2 value of 0.77 in predicting soundscape quality, its generalizability is limited due to its construction based on controlled laboratory data, lacking validation in real-world settings. To enhance predictive accuracy and generalizability, researchers are increasingly exploring the integration of additional variables, including objective landscape metrics (e.g., spatial landscape indicators) and subjective responses (e.g., perception of sound sources), into model developments. For instance, Romero created a linear regression model to predict the soundscape quality of urban waterfronts based on sound pressure level, roughness, geometry and spatial configuration parameters of landscape, and percentage of landscape elements as input variables, could achieve a moderate R^2 value of 0.41. Ricciardi combined loudness, visual amenity and perception of sound sources and could achieve a higher R^2 value of 0.52, which was much higher than the R^2 value of 0.21 yielded by physical model. Also, probabilistic approach has been adopted to predict soundscape evaluation based on physical sound properties, psychological and personal factors on outdoor soundscape evaluation. Tse et al. developed an ordered logit model using A-weighted equivalent continuous sound pressure level (LA_{eq}), perception of sound sources (e.g., perception of birdsong), respondents' characteristics (e.g., age), location and visual comfort to predict soundscape evaluation of urban park. Maristany introduced a fuzzy logic model combining four factors - sharpness, loudness, L_{10}-L_{90}, and center of gravity (CoG) or LC_{eq}-LA_{eq}, to predict the soundscape quality of an urban open space. However, these models generally suffer from some shortcomings. They did not fully take into account the evidence that soundscape quality predictions are typically influenced by a multitude of sensory factors (Lin et al., 2025). In addition, it is evident that significant interactions exist among soundscape influencing factors, with most efforts focusing on audiovisual interactions (Li and Lau, 2020; Schwartz et al., 2004). Such complex interactions add layers to perceptual outcomes (Jeon and Jo, 2020); however, traditional linear assumptions fall short in capturing these multidimensional, dynamic relationships, limiting the explanatory power of simple linear regression models (Lionello et al., 2020). Consequently, more flexible modeling approaches are needed to capture nonlinear relationships and improve the accuracy of soundscape quality predictions.

With the development of machine-learning technologies and the speedy enhancement in computational power, an increasing number of studies have started applying machine-learning methods for directly predicting soundscape evaluation ratings. Various machine algorithms such as artificial neutral network (ANN), random forest (RF) have been utilized to achieve promising predictive performance. For example, in addition to developing a linear regression model, Romero (Romero et al., 2016) also constructed an ANN model to predict the soundscape quality of urban waterfronts by incorporating more physical parameters and landscape spatial indicators. This approach achieved a significant improvement, with an R^2 value of 0.90, which is notably superior to the 0.41 obtained by the linear regression model. However, this model has limited applicability, primarily suitable for waterfront areas with low building density, and lacks applicability in densely populated urban environments. In addition, Zhao et.,al (2022) constructed a gradient boosted regression trees (GBRT) model to predict urban soundscape quality by only using 28 visual features automatically captured using computer vision technology. The resulting R^2 value of 0.68 demonstrates the model effectiveness in predicting soundscape quality based on visual cues. But this model only considers the impact of visual factors, ignoring other key elements such as auditory factors, which may result in an incomplete prediction of soundscape quality. Wang et.,al (2022) combined acoustic features (e.g., LA_{eq} and proportion of sound source), geospatial data (e.g., proportion of forest), personal factors (e.g., Age) and time factors (e.g., seasonal) to create a random forest to predict soundscape comfort, with a moderate high predictive performance (i.e., F1 score 0.64). While it focuses primarily on large-scale visual landscape features, overlooking the visual perception from an individual perspective, which may lead to insufficient detail capture in the model. While these models have shed some lights on the importance and directional impact of various features in machine-learning, they have often been considered as "black boxes" with limited transparency into their model details. Lack of transparency limits understanding of the significance of various factors and their models, and further hinders model development.

Furthermore, all the foregoing models ignore the influence of microclimatic factors and people's thermal perception, which can play a significant role in soundscape experience. Previous studies have shown that thermal perception significantly affects soundscape through its influence on both physiological and psychological processes, often intensified by multisensory interactions (Du et al., 2023; Geng et al., 2022). High-temperature environments can induce physiological stress, reducing individuals' ability to tolerate environmental stimuli (Silva et al., 2019; Tyler et al., 2024). Elevated temperatures negatively impact emotional states, leading to irritation and anxiety, which enhance sensitivity to unpleasant sounds (e.g., traffic noise) and diminish the restorative effects of natural sounds (e.g., birdsong). These combined effects not only degrade overall soundscape evaluation but also underscore the complex interaction between thermal and auditory factors. Despite this understanding, there is a lack of quantitative research to define the thresholds and specific contributions of thermal-sound interactions, leaving critical gaps in the prediction and optimization of soundscape quality under varying thermal conditions.

To address these issues, the primary objective of this study is to formulate a machine-learning model that can accurately predict the soundscape quality of an open space by considering significant aural and visual factors, as well as the influence of thermal factors. Specifically, this study also aims to verify our underlying premise that non-linear machine-learning models provide better prediction performance than traditional linear statistical approaches. To circumvent the common shortcomings of machine-learning models in transparency and interpretations, SHapley Additive exPlanations (SHAP), which is an algorithmic framework based on Shapley values from Game Theory, has been proposed to supplement the developed machine-learning models. This provides a unified and mathematically grounded approach to estimate the contribution of each feature to a model's output prediction, thereby enhancing interpretability of black box nature of common machine-learning models. Soundscape quality, defined as an evaluation of whether a soundscape is perceived as "good" or "bad," provides a concise yet comprehensive evaluation of soundscape, making it the primary focus of this study. It is considered superior to other descriptors like acoustic comfort, soundscape quality or pleasantness because it more comprehensively and directly describes the acoustic environment of open space quality (Aletta et al., 2016b; Axelsson, 2015). Compared to other descriptors such as acoustic comfort, pleasantness, or tranquillity, soundscape quality demonstrates greater stability and comparability across different types of open spaces, making it particularly suitable for large-scale environmental assessments. Moreover, this indicator not only captures the overall characteristics of the acoustic environment but also exhibits higher consistency and reliability across different cultural contexts (Jeon et al., 2018). Ranking the importance of individual multisensory determinants within the optimal machine model and evaluate their positive and negative effects on soundscape quality. Finally, revealing the relationships between individual determinants and soundscape quality, as well as the potential interaction effects and the resulting nature of interactions between these determinants. These findings provide practical guidance for open space urban designers and planners on the effective ranges of factors that produce optimal soundscape quality.

2.5 Conclusion

There are three major research gaps as shown in the followings:

First, there is a lack of comprehensive studies to determine whether and how multisensory and cross-modal determinants influence soundscape evaluation. Although multisensory and cross-modal interactions have been reported in soundscape research, these findings are mostly fragmented.

Second, the impact of landscape contextual factors, such as functional types and ongoing activities, has not been thoroughly explored. In high-density urban open spaces, without considering the role of micro-scale functional spaces (e.g., rest areas, play areas), it is challenging to fully understand and accurately evaluate the diverse needs and expectations for soundscape evaluation.

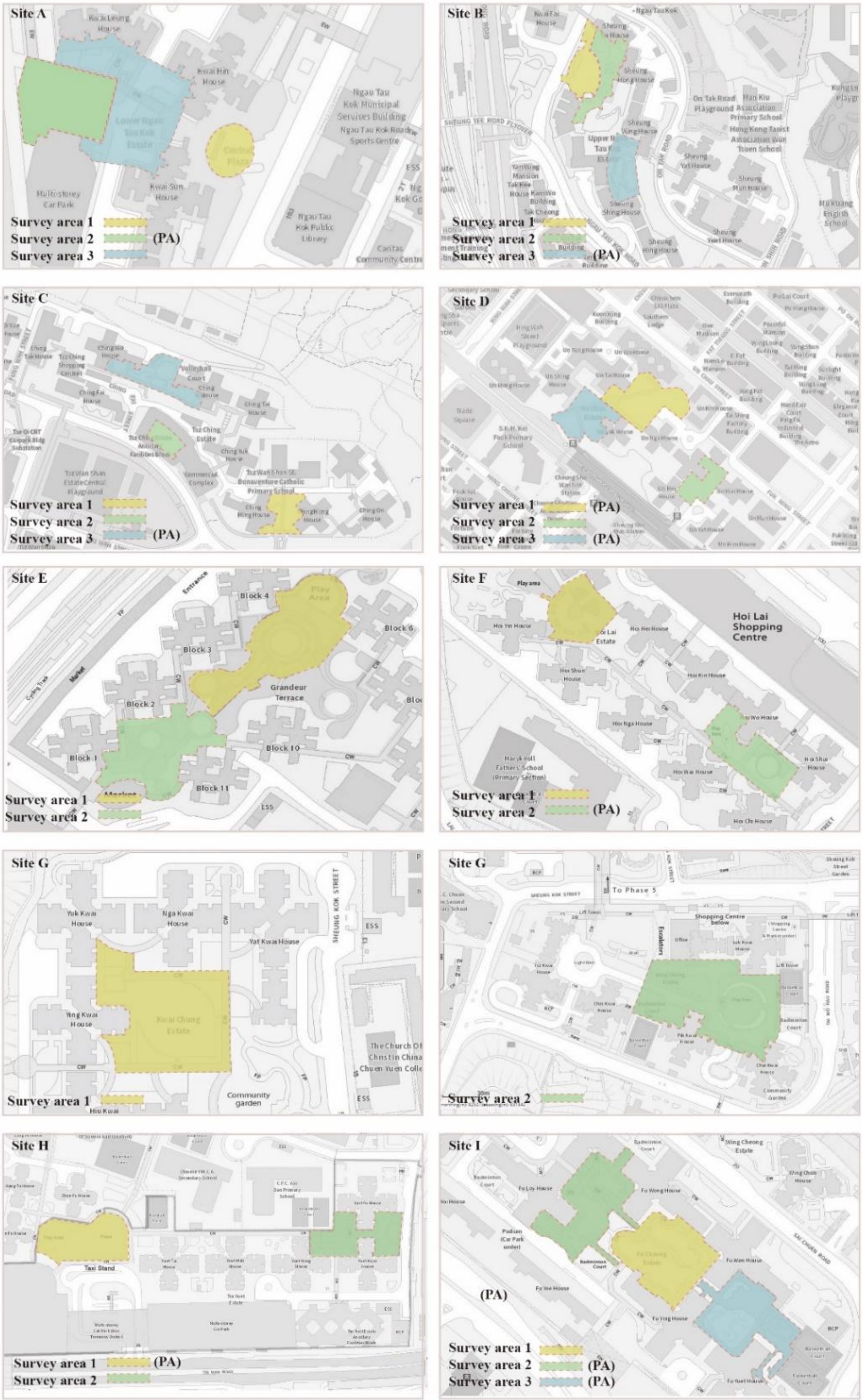
Third, there is also a lack of accurate soundscape prediction models based on nonlinear relationships. Current soundscape prediction models primarily rely on linear assumptions, which are inadequate for capturing the complex and dynamic interactions between multisensory factors, environmental attributes, and soundscape evaluation. Although some machine learning methods have been applied to soundscape prediction, they often lack model transparency, limiting the interpretability of the influence of various factors.

Chapter 3 Methodology

This study adopts a multi-method comprehensive design to explore the influence of multisensory and multifunctional factors on the soundscape quality of urban open spaces, with a particular focus on the unique context of public housing estates. The research methods include questionnaires, field measurements, soundwalks, and sound maps. Public housing estates, with their rich audiovisual resources and diverse micro-functional spaces, provide an ideal setting for this study. The questionnaire aims to capture respondents' subjective perceptions of sound, visual, and microclimatic environments, while field measurements utilize real-time sound level meters, panoramic cameras, and micro-climate stations to collect objective data on the physical environment within the open spaces of public housing estates. This combination establishes a robust foundation for analyzing the determinants of soundscape quality. Soundwalks involve guiding participants through a series of sequential walking routes to evaluate the soundscape quality of various micro-functional spaces within public housing estates, with a particular emphasis on examining how functional types and activity characteristics influence soundscape perceptions. Sound maps, developed through numerical simulation, spatially depict the objective acoustic environment of the open spaces. These maps, combined with subjective perception data, provide qualitative insights into the interactions between multisensory and multifunctional factors. By focusing on public housing estates as unique urban open spaces within compact cities, this methodological approach lays a solid scientific foundation for uncovering the mechanisms influencing soundscape quality and devising effective optimization strategies.

3.1 Questionnaire surveys and on-site measurements

Hong Kong as a coastal city has a humid subtropical climate with hot, long and humid summers, as well as mild and short winters. Communal open space (COS) is commonly found in PHEs in Hong Kong, which are predominantly used by residents and shared with other visitors as well as residents of neighboring developments. As some public housing estates are located in high-dense urban areas, densely packed high-rise towers further aggravate the thermal comfort problems in COS induced by heat island effects during hot seasons. In addition, high-rise towers frequently block the scenery views from COS. For COS located on ground, they are constantly exposed to noise and air pollution and the high-density as well as high-rise of building morphology can also magnify traffic noise problems. Accordingly, COS in public housing estates (PHEs) is regarded as suitable survey sites for investigation of acoustic and non-acoustic factors influencing the soundscape quality in public open space. A total of 23 COSs were selected from nine public housing estates (PHEs) in Hong Kong (Site A-I), which included 10 play areas and 13 sitting-out areas (see Figure below). The survey sites were chosen such that they covered a wide range of environmental conditions, including varying levels of exposure to traffic noise, as well as different visual and thermal conditions. In addition, they covered functional diversity of COS, which included play areas, known for higher activity and noise levels, and sitting-out areas, intended for relaxation and quieter use. This approach enabled us to examine how different types of functional space influence soundscape quality under similar external environmental conditions.



Note: PA represents the function of the investigation areas as play areas, and the others are sitting-out areas.
Different color tones represent the different survey areas of various sites.
(i.e., yellow represents the survey area 1,green represents the survey area 2, blue represents the survey area 3)

Figure 3-1 Site maps showing the surveyed areas in COS within the nine PHEs

The form of questionnaire surveys followed the guidelines laid down by ISO/TS 12913-2:2018 Standard for data collection and reporting requirements of soundscape but with additional questions on thermal sensation and acceptability. Respondents were randomly chosen within the predefined boundaries of each site during each survey session. A structured questionnaire was employed with details provided in Table 3-1, which outlines the key questions and their corresponding rating scales.

Table 3-1 A Summary of Key Questions and Their Corresponding Rating Scales

Attribute	Descriptions	Rating Scale
Sound sources identification	Describe the perceived dominance of specific sound sources (vehicle sounds, train sounds, human sounds, birdsong, rustling leaves) using an 11-point verbal scale.	11-point verbal scales: 0-'Not dominant at all, 5-'Netural', and 10-'Compeletely dominant'
Visibility of landscape features	Describe the visibility of landscape features (road, building, greenery, sky) using an 11-point verbal scale.	11-point verbal scales: 0-'Not dominant at all, 5-'Netural', and 10-'Compeletely dominant'
Perceived Affective Quality (PAQ)	Rate the perceived affective quality (PAQ) using eight 11-point scales of soundscape descriptors (Pleasant, Chaotic, Vibrant, Uneventful, Calm, Annoying, Eventful, Monotonous).	11-point verbal scales: 0 as 'Strongly Disagree', 5 as 'Neutral', and 10 as 'Strongly Agree'
Overall Quality Ratings	Rate the quality of COS, soundscape, and landscape using an 11-point verbal scale.	11-point verbal scales: 0-'Very Bad', 5-'Netural', and 10-'Very Good'
Thermal Assessments	Evaluate thermal sensation using a 7-point ASHRAE PMV scale and rate thermal comfort and acceptability using 11-point scales.	7-point ASHRAE PMV scale for sensation (i.e. –3-'Cold', –2-'Cool', –1-'Slightly Cool', 0-'Neutral', 1-'Slightly Warm', 2-'Warm', 3-'Hot'); 11-point scales for comfort (0-'Extremely Uncomfortable', 5-'Comfortable', and 10-'Extremely Comfortable') and acceptability (0-'Extremely Unacceptable', 5-

		'Acceptable', 10-'Extremely Acceptable')
Personal Characteristics	Provide information on age, gender, occupation, and self-assessed auditory capacity.	N/A

Based on ISO/TS 12913-3:2019, *Pleasantness* and *Eventfulness* can be determined by Eqns. (1) and (2) based on the eight perceived affective quality values collected from the questionnaire responses as follows.

$$PL = (p - a) + cos45^{\circ} \cdot (ca - ch) + cos45^{\circ} \cdot (v - m) \quad \text{and} \qquad (1)$$

$$EV = (e - u) + cos45^{\circ} \cdot (ch - ca) + cos45^{\circ} \cdot (v - m) \qquad (2)$$

where p is pleasant, a is annoying, ca is calm, ch is chaotic, e is eventful, u is uneventful, v is vibrant, and m is monotonous. *Pleasantness* is related to how pleasant or unpleasant the environment is judged and *Eventfulness* is represented by how eventful or uneventful the acoustic environment is perceived to be.

At the beginning of the questionnaire survey, an interviewer asked each respondent to listen to the surrounding sound environment for about one-minute at the start of the questionnaire survey. One-minute binaural sound was recorded at the ear-canal positions with two microphones (Brüel & Kjær Type 4101) connected to a portable analyzer (Brüel & Kjær Type 2270) for registering properties of sounds heard by individual respondents. The recording staff took pictures by following the respondent's orientation and viewing direction (See Figure 3-3). The corresponding sound recordings and photos were later matched with each respondent’s questionnaire responses.

Specifically, sharpness (acum) was computed per DIN 45692 by first deriving a specific-loudness distribution on the Bark scale using the ISO 532-1 (Zwicker) loudness front-end, then applying the standardized high-frequency weighting. Roughness (asper) followed the Zwicker model (see Zwicker & Fastl, 1990), implemented with the ISO 532-1 time-varying specific-loudness front-end: from absolutely calibrated binaural waveforms we obtained a roughness time series that emphasizes ~20–300 Hz amplitude modulations (maximum around ~70 Hz), and we reported the average over the entire recording. Fluctuation strength (vacil) used a Zwicker-et-al.–based formulation (see Zwicker & Fastl, 1990) with the same ISO 532-1 time-varying loudness front-end, emphasizing slow modulations < 20 Hz (characteristic maximum near ~4 Hz), and averaged over the entire recording. In addition, the panoramic images were later undergone semantic segmentation processing to yield layered landscape metrics at varying levels of detail (See Fig. 3-2), including pixel-level attributes (e.g., standard deviation of Hue), object-level features (e.g., count of people present), and semantic-level elements (e.g., proportion of greenery). Upon our subsequent statistical analyses, significant correlations were observed between people’s subjective visual perception and objective landscape metrics. For instance, the Pearson correlation coefficient values between proportion of greenery and visual perception of greenery was 0.243** ($p<0.001$), between the proportion of sky and the visual perception of sky was 0.193** ($p<0.001$), and between the number of vehicles and visual perception of roads was 0.408** ($p<0.001$). Such high correlations between physical metrics and subjective perceptions suggest the validity of using objective environmental indicators as proxies for perceptual attributes.

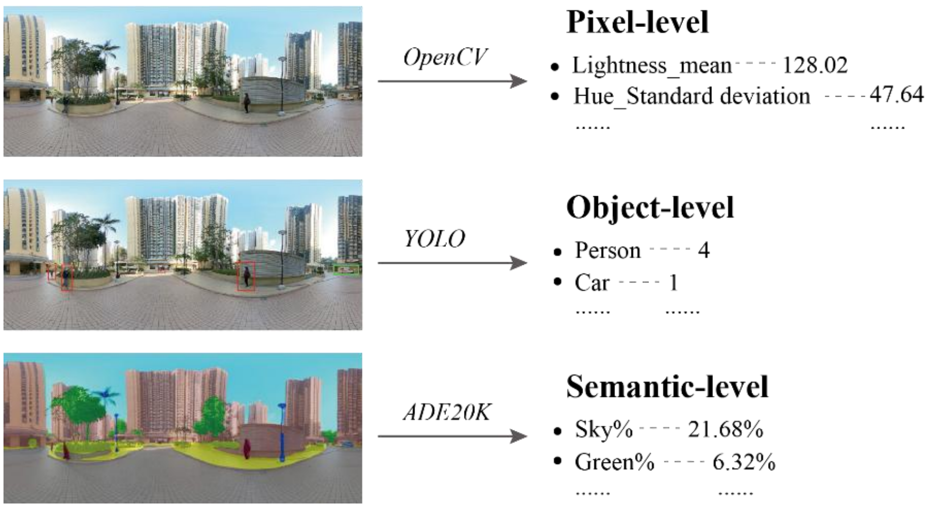


Figure 3-2 Different levels of visual features deriving from semantic segmentation

A mobile microclimate station had also been assembled to include instrument for measuring outdoor air temperature, relative humidity, wind speed, globe temperature and solar radiation intensity of the surveyed sites (see Table 3-2 and Figure 3-4). Finally, these physical parameter values were used as input to the Rayman model for computing the corresponding physiological equivalent temperature (PET).

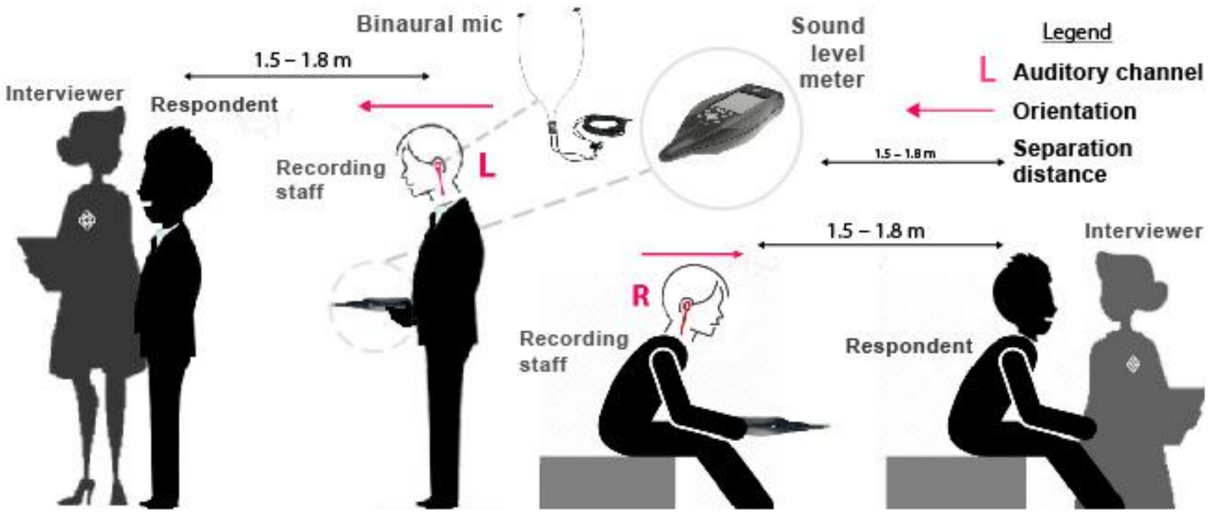


Figure 3-3 Diagram indicating the relative positions of the interviewer, respondent and recording staff during a questionnaire-survey carried out in a public open space

Table 3-2 Specification details of the measurement instrument of the mobile microclimate stations

Instrument	Measurement parameter	Operating range	Measurement range	Accuracy
HOBO U23 Prov2 Temperature/Relative Humidity Data Logger with weatherproof temperature and relative humidity sensors	Air temperature	−40 °C to 70 °C with a resolution of 0.02 °C at 25 °C	−40 to 70 °C	±0.21 °C
	Relative humidity	−40 °C–70 °C with a resolution of 0.03 °C	0 to 100%	±2.5 °C
Dantec low velocity flow analyzer with Robust temperature-compensated velocity probe (54T35)	Wind speed	−20 °C and 80 °C	0.01 m/s to 30 m/s	±2% (0.2–20 m/s) ±5% (20–30 m/s)
Globe thermometer (consisted of a 40 mm grey table tennis ball and temperature sensor)	Globe temperature	−20° to 70 °C	−20° to 70 °C	±0.35 °C
Silicon Pyranometer	Solar radiation	−40 °C–75 °C	0 and 1280 W/m2	±5%

Figure 3-4Mobile microclimate station in different survey sites

3.2 Soundwalks

Due to resources constraints, we defined three major criteria for the selection of open spaces and survey spots for soundwalk. Firstly, the survey stops were required to cover a wide range of sound sources (traffic, human, animals, and machines) and visual scenarios with varying degrees of openness, all belonging to one of the designated microscale functional types. Secondly, only open spaces located within residential housing estates (RHEs) were chosen to exclude the impacts of neighborhood functional type. Thirdly, the chosen estates needed to be in urban areas close to traffic roads, with road traffic as the major external noise source and human activities as the major internal source. Finally, the selected open spaces were required to be multifunctional, including sitting-out areas, children's play areas, and circulation areas. These criteria ensure a diverse range of ambient sound sources, and visual scenarios, offering rich opportunities to study the acoustic and contextual factors influencing the soundscape quality in open spaces.

Four RHEs in Hong Kong, labelled A to D, were selected for setting up four soundwalk routes as depicted in Figure 3-5. These routes either fully or partially include the paths that residents commonly walk along in their daily routines. A number of stops were identified along selected routes to cover a wide variety of microscale functional space, hereafter referred to as "functional spaces". Three major types of functional space were selected as survey sites: play areas, sitting-out areas and circulation areas (or path area). What worth noting is that, the same functional space may host different types of activities at various times of the day. For example, in play areas, elders often engage in physical exercises in the morning, while children play in the afternoon after school.

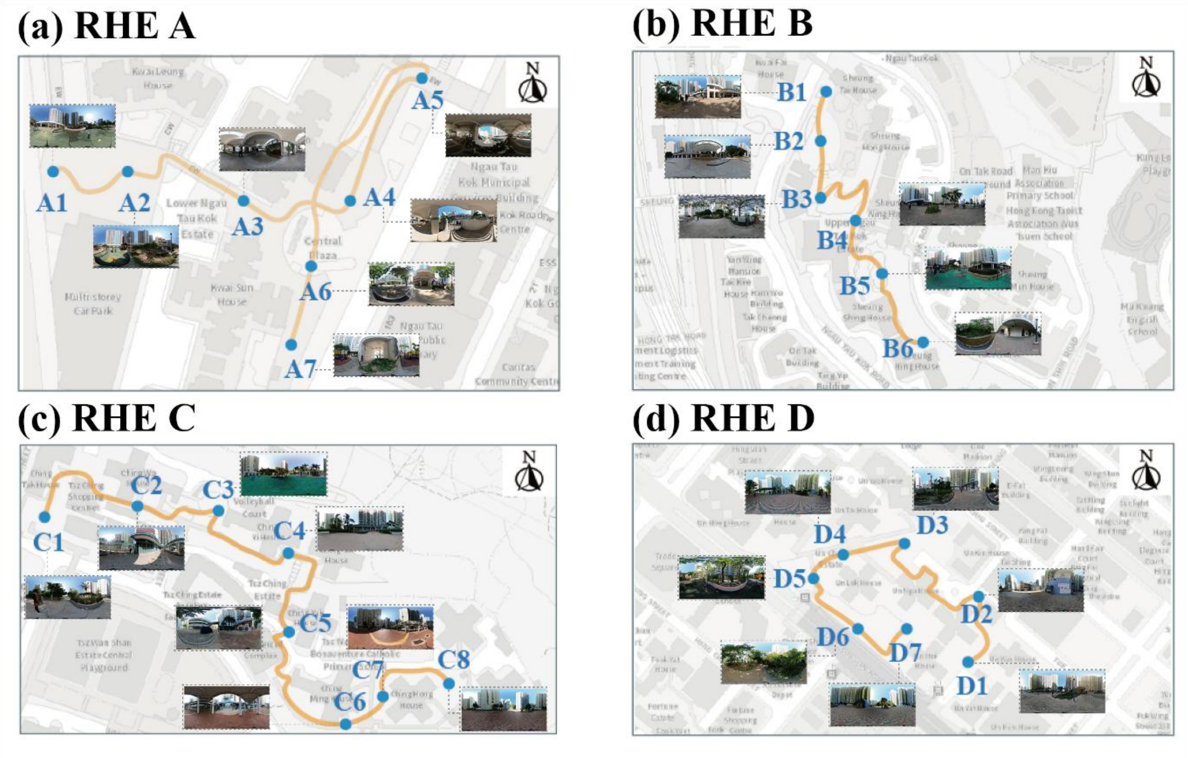


Figure 3-5 Four soundwalk routes and stops selected in four residential housing estates

Our soundwalk approach was generally aligned with the assessment criteria specified in S 5.2 of ISO/TS 12913-2:2018, enabling us to collect field data that captured the participants' perceptual responses to various attributes of the acoustical environment, including loudness, sound source dominance, affective qualities, and compatibility between soundscape and landscape. The conducted soundwalk trips were conducted during fine weather across three-time sessions: morning (am), afternoon (pm), and evening (eve). Each soundwalk lasted approximately 40 minutes. During each soundwalk, a research staff guided a group of 4 to 6 participants along a pre-determined route, acting as the moderator. The group walked to and from specific locations, stopping at several selected points along the way. During the soundwalk trips, the moderator of the soundwalk group recorded one-minute binaural audio samples at each stop of the soundwalk route using two in-ear microphones (Brüel & Kjær Type 4101) connected to a hand-held sound level meter (Brüel & Kjær Type 2270). At each stop along the two-way soundwalk route, two audio samples were collected.

In addition, panoramic images capturing the views experienced by participants at the selected locations were recorded using a GoPro Max 360 Action Camera. This camera features dual lenses capable of capturing 360-degree images and videos with a resolution of up to 16.6 megapixels for photos and 5.6K at 30fps for videos. Given the back-and-forth nature of soundwalk, the imagery for each recording point was primarily focused on capturing the 180° field of view facing forward. Semantic segmentation techniques were applied to the captured images to analyse visual information of natural elements like greenery and sky. Specifically, the percentage of pixels representing visual features in a scene was calculated by dividing the number of pixels of these elements by the total number of pixels in the photograph. Given the view of the sky in open spaces is frequently obstructed by high-rise buildings in densely populated urban areas, relying solely on the percentage of visible sky does not adequately assess the openness of a space. Consequently, following the definition given by Jeon et al., both "open area" and "percentage of sky" were used to measure visual openness. The analysis of the image information at each location helped identify obstacles blocking the view. An open area was then defined as the clearly visible space within the closed boundary formed by buildings and other obstacles.

At each stop, participants were asked to carefully listen to the acoustic environment for about one minute and then completed a structured questionnaire. Regarding the perception of sound environment, participants were asked to: 1) rate perceived loudness on a scale from 0 to 10; 2) indicate the presence of specific sounds using a binary scale (0 or 1), where 0 means a sound, such as birdsong, was not perceived, and 1 means it was perceived; and 3) identify the most dominant sound, rating it as 1 if perceived as the most dominant, with all other sound sources rated as 0. Using the same rating scale, participants were asked to evaluate their perception of greenery, sky, buildings, and roads, and to identify the most dominant landscape feature at each stop. Additionally, they were asked to rate the overall quality of soundscape on a scale from 0 to 10. Personal characteristics of the participants, such as gender, age, and self-reported noise sensitivity, were also collected.

3.3 Sound maps

A series of physical measurements were also conducted to create sound maps. These maps facilitate the visualization of spatial and temporal variations in the physical and psychoacoustic properties for the surveyed stops. Similar to the soundwalk setup, the sound map surveys were conducted during three distinct periods each day: morning (10:00-11:00), afternoon (14:00-15:00), and evening periods (16:30-17:30). During the measurement process, one research staff remained at the reference point with a binaural microphone to conduct continuous recordings. Simultaneously, another research staff moved to various stops within the measurement areas to take one-minute binaural recording at each location. The operation at the reference point was only completed once the one-minute acoustic recording has been captured at all selected spots surrounding the reference point. The consistent location of the reference points, compared to the brief one-minute measurement duration at each spot, allowed the recordings to effectively capture sporadic acoustic events. These events were particularly noticeable during transitions from one measurement spot to the next. The total duration of the measuring operation across the three reference points amounted approximately 50 minutes. The measurement procedures followed the requirements specified in Annex D of ISO/TS 12913-2:2018. Subsequently, the binaural measurement points were mapped onto the site plan, which was retrieved from the HKMS 2.0 website, with a grid resolution of 7.5 meters. Kriging-based spatial interpolations between measurement points were performed using Matlab to generate the sound maps. The colour legends on these maps followed the jet colormap scheme, which range from blue to red, passing through shades of cyan, yellow and orange.

Chapter 4 A preliminary exploration of key factors influencing soundscape

4.1 Exploring the impact of determinants -- multisensory view

4.1.1 Personal and acoustical characteristics of questionnaire survey

A series of field measurements was conducted in conjunction with questionnaire surveys in three-time sessions from 09:00 to 18:30 during weekdays and weekends between August 2021 and March 2023. Table 4-1 shows the personal details of all the respondents surveyed in the nine individual sites. About 46 percent of the respondents were men, and about half were between ages of 20-59. Their average self-assessed auditory capacity was higher than ’Good‘, and their average self-reported health condition was better than ’Fair’.

Table 4-2 shows a summary of the major site characteristics and sound environment of nine survey sites. As most of our survey COSs were located in urban centers, they were closely surrounded by high-rise buildings and busy traffic roads, resulting in high and constant levels of background noise throughout the day. In addition, they were occupied by large crowds of people for socializing, leisure and rest. Many COSs were provided with greenery, which attracted birds and provided shade.

Table 4-1 A summary of personal characteristics of the respondents

Description	Number of Respondents
GENDER	
Male	800 (45.7%)
Female	949 (54.3%)
AGE	
Under 20	289 (16.5%)
20-29	215 (12.3%)
30-39	246 (14.1%)
40-49	174 (10.0%)
50-59	185 (10.6%)

≥60	640 (36.6%)
OCCUPATION	
Student	349 (20.0%)
Employed	528 (30.2%)
Retired	561 (32.1%)
Home care	289 (16.5%)
Others	22 (1.3%)
MEAN†	
NOISE SENSITIVITY	2.40
No. of Respondents	**1749**

Table 4-2 A summary of major site and acoustical characteristics of the survey areas of questionnaire survey

PHEs	**A**			**B**		
	A1	**A2**	**A3**	**B1**	**B2**	**B3**
Areas (m²)	560	570	600	2010	2240	1540
Site characteristics	Ground, adjacent to major trunk road	Podium, facing highway and MTR line	Ground, inner trunk road	Ground, adjacent to major trunk road	Mezzanine, adjacent to green slopes	Podium, against slope and sunken from trunk road above
Perceived dominance	Vehicle (μ=6.63)	Vehicle (μ=5.43)	Vehicle (μ=5.58)	Vehicle (μ=5.21)	Human (μ=4.90)	Human (μ=6.13)
Soundscape quality	μ=5.11, SD=1.74	μ=5.65, SD=1.84	μ=5.97, SD=1.40	μ=5.41, SD=2.10	μ=5.44, SD=1.87	μ=6.42, SD=1.76
Overall open space quality	μ=5.59, SD=2.01	μ=6.50, SD=1.32	μ=6.51, SD=1.49	μ=5.66, SD=2.36	μ=6.15, SD=1.49	μ=6.87, SD=1.75
LA_{eq} (dBA)	μ=69.65, SD=1.58	μ=68.92, SD=2.24	μ=66.34, SD=1.62	μ=69.83, SD=2.40	μ=64.70, SD=2.38	μ=65.64, SD=3.27

PHEs	**C**			**D**		
	C1	**C2**	**C3**	**D1**	**D2**	**D3**
Areas (m²)	3360	880	2180	3360	1490	3200

Site characteristics	Podium, facing major trunk road	Podium, facing major trunk road	Upper podium, against slope and seclude from residents and road traffic	Ground, near shopping center	Ground, adjacent to pedestrianized zone	Ground, facing plaza and set back from trunk road
Perceived dominance	Vehicle (μ=4.44)	Human (μ=5.07)	Human (μ=3.88)	Human (μ=4.94)	Human (μ=6.10)	Human (μ=6.05)
Soundscape quality	μ=6.12, SD=2.19	μ=5.63, SD=1.65	μ=6.20, SD=1.47	μ=5.90, SD=1.80	μ=5.96, SD=1.59	μ=5.42, SD=1.85
Overall open space quality	μ=6.98, SD=1.81	μ=6.32, SD=1.55	μ=6.45, SD=1.78	μ=6.65, SD=1.49	μ=6.20, SD=1.88	μ=6.23, SD=1.96
LA_{eq} (dBA)	μ=64.77, SD=2.23	μ=67.80, SD=2.23	μ=63.37, SD=3.02	μ=68.17, SD=3.76	μ=65.56, SD=1.41	μ=64.47, SD=2.11

PHEs	**E**		**F**		**G**	
	E1	**E2**	**F1**	**F2**	**G1**	**G2**
Areas (m^2)	2870	2771	1342	1374	3429	3729
Site characteristics	Ground, surrounded by planters, enclosed by buildings.	Ground, surrounded by planters, enclosed by buildings. Covered by plants and canopies	Ground, enclosed by PHE buildings	Ground, enclosed by PHE buildings, facing major trunk road	Upper Deck, enclosed by PHE buildings	Upper Deck, enclosed by PHE buildings, open view in one direction
Perceived dominance	Birdsong (μ=4.17)	Birdsong (μ=4.09)	Birdsong (μ=4.14)	Human (μ=3.95)	Birdsong (μ=4.61)	Human (μ=4.42)
Soundscape quality	μ=6.41, SD=1.85	μ=5.89, SD=1.76	μ=6.14, SD=1.82	μ=6.26, SD=2.12	μ=6.32, SD=1.86	μ=6.13, SD=1.85
Overall open space quality	μ=6.47, SD=1.82	μ=5.79, SD=1.68	μ=6.42, SD=1.92	μ=6.23, SD=1.89	μ=6.47, SD=1.96	μ=6.60, SD=1.80
LA_{eq} (dBA)	μ=61.47, SD=2.88	μ=65.38, SD=2.52	μ=64.70, SD=2.48	μ=63.21, SD=3.36	μ=63.21, SD=2.13	μ=63.01, SD=4.12

PHEs	**H**		**I**		
	H1	**H2**	**I1**	**I2**	**I3**
Areas (m^2)	3139	2167	2442	2446	4058

Site characteristics	Ground, adjacent to the major mall and the bus terminal	Ground, adjacent to a school, major trunk road and a LRT platform	Ground, enclosed by PHE buildings	Ground, adjacent to a multi-story car park, enclosed by PHE buildings	Ground, adjacent to a trunk road
Perceived dominance	Human (μ=5.44)	Birdsong (μ=5.08)	Human (μ=4.58)	Human (μ=5.14)	Human (μ=3.74)
Soundscape quality	μ=6.37, SD=1.54	μ=6.10, SD=1.79	μ=6.18, SD=1.76	μ=6.16, SD=1.65	μ=6.65, SD=1.62
Overall open space quality	μ=6.47, SD=1.53	μ=6.26, SD=1.75	μ=6.53, SD=1.88	μ=6.51, SD=1.83	μ=6.82, SD=1.76
LA_{eq} (dBA)	μ=65.16, SD=3.22	μ=62.46, SD=2.75	μ=66.03, SD=3.25	μ=67.37, SD=3.43	μ=63.85, SD=2.43

4.1.2 Bivariate analysis of aural-visual-thermal determinants

Table 4-3 show the summary of mean ratings for the quality of different types of environments in 9 estates. Before conducting statistical analyses, the data were subjected to normality tests to assess whether the assumptions of parametric methods were satisfied. The results indicated that most variables met the normality assumption, while non-normally distributed data were treated with appropriate non-parametric tests. Figure 4-1 Show the Pearson bivariate correlation between soundscape quality and other sensory. The correlation heat map reveals a significant positive relationship between soundscape quality and pleasantness ($r = 0.41$), indicating that higher levels of pleasantness are associated with better perceived soundscape quality. Additionally, soundscape quality shows a moderate positive correlation with birdsong ($r = 0.28$), suggesting that natural sound sources may enhance soundscape perception. In contrast, negative correlations are observed with road noise ($r = -0.16$) and human sounds ($r = -0.14$), implying that anthropogenic noise may detract from perceived soundscape quality. Visual quality also exhibits a moderately positive correlation with soundscape quality ($r = 0.40$), highlighting the role of visual elements in improving soundscape evaluations. Thermal-related variables, including thermal comfort ($r = 0.20$) and thermal acceptability (r = 0.2), also show positive correlations with soundscape quality. However, further investigation is needed to clarify the indirect effects and interactions among these variables to better understand the multisensory influences on soundscape perception.

Table 4-3 Summary of mean ratings for the quality of different types of environments in 9 estates

		Acoustic Environment	**Visual Environment**	**Thermal Environment**	
		Soundscape quality	**Visual quality**	**Thermal comfort**	**Thermal acceptability**
PHEs	**Site**	Mean (μ)	Mean (μ)	Mean (μ)	Mean (μ)
A	**A1**	5.11	6.04	4.18	5.25
	A2	5.65	6.45	4.74	5.37
	A3	5.97	6.14	7.59	7.42
B	**A1**	5.41	6.06	4.89	5.14
	A2	5.44	6.15	6.87	7.15
	A3	6.42	6.60	6.71	7.16
C	**A1**	6.12	6.38	6.56	6.90
	A2	5.63	6.68	4.88	5.14
	A3	6.20	7.00	5.59	6.04
D	**A1**	5.90	6.49	4.88	5.27
	A2	5.96	5.92	5.76	6.18
	A3	5.42	5.88	5.72	5.81
E	**A1**	6.18	6.48	3.66	4.19
	A2	6.16	6.13	4.69	5.33
	A3	6.65	6.61	5.79	6.09
F	**A1**	6.41	6.57	5.64	5.73
	A2	5.89	6.41	5.20	5.28
G	**A1**	6.14	6.64	4.27	4.83
	A2	6.26	6.67	6.27	6.34
H	**A1**	6.32	6.27	5.08	5.57
	A2	6.13	6.63	6.06	6.29
I	**A1**	6.37	6.42	4.52	5.14
	A2	6.10	5.95	5.16	5.79

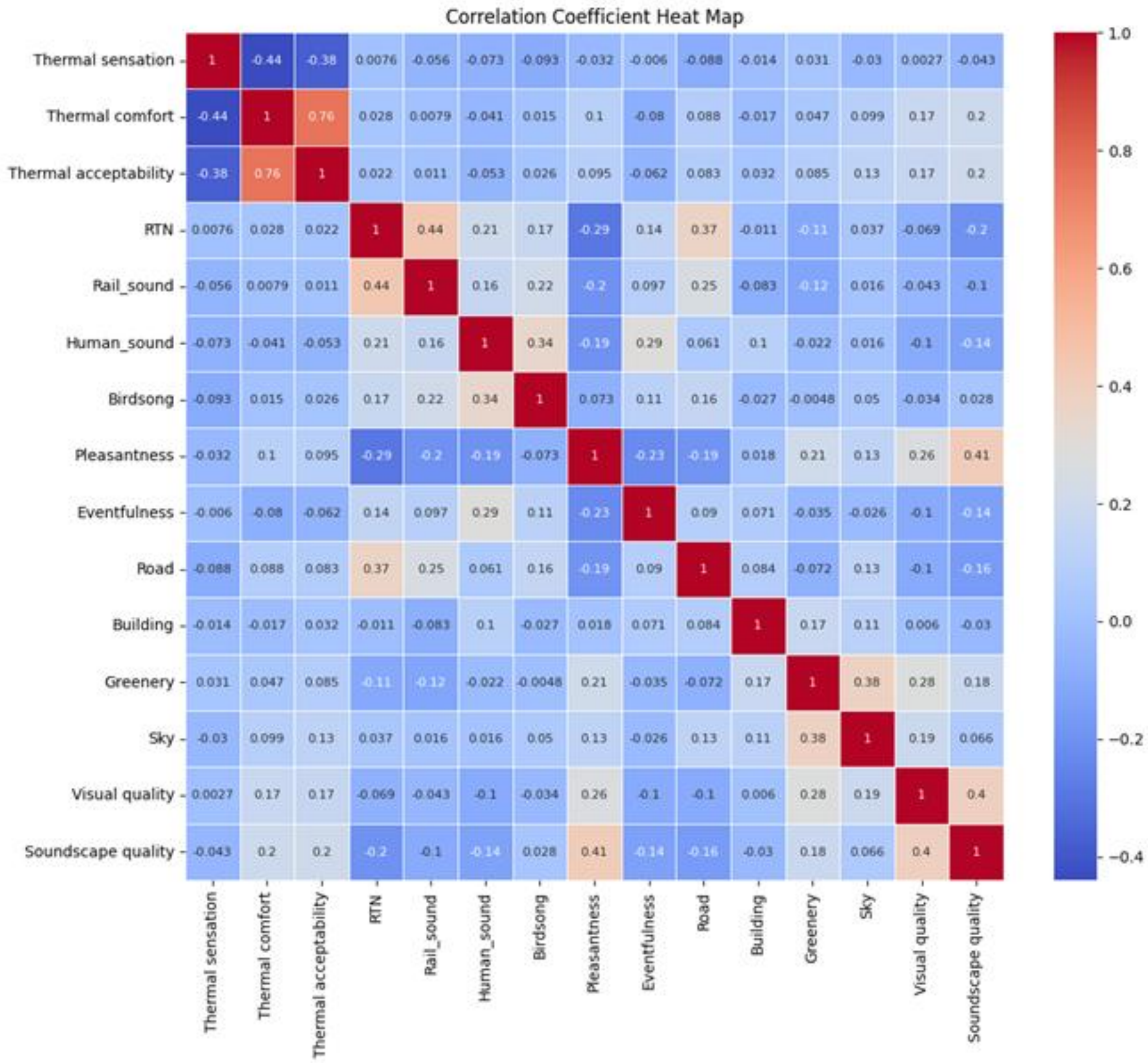


Figure 4-1The correlation heat map of multisensory factors

4.2 Exploring the impact of determinants – multifunctional view

4.2.1 Personal and acoustical characteristics of soundwalk

Participants who took part in the soundwalks were mainly students or acquaintances recruited from one university in Hong Kong. All of them were Hong Kong residents, with a balanced gender distribution across the sample. Table 4-4 shows a summary statistic of the participants' characteristics and Table 4-5 show a summary of the characteristics of the four survey sites.

Table 4-4 A summary statistic of the participants' characteristics

Description	RHE A	RHE B	RHE C	RHE D	Total (%)
GENDER					
Male	12 (44.4%)	16 (59.3%)	16 (57.1%)	12 (44.4%)	56 (51.4%)
Female	15 (55.6%)	11 (40.7%)	12 (42.9%)	15 (55.6%)	53 (48.6%)
AGE					
Under 20	8 (29.6%)	0 (0.0%)	0 (0.0%)	2 (7.4%)	10 (9.2%)
20-29	19 (70.4%)	17 (63.0%)	20 (74.1%)	20 (74.1%)	77 (70.6%)
30-39	0 (0.0%)	9 (33.3%)	5 (18.5%)	5 (18.5%)	19 (17.4%)
40-49	0 (0.0%)	0 (0.0%)	1 (3.7%)	0 (0.0%)	1(0.9%)
50-59	0 (0.0%)	1 (3.7%)	1 (3.7%)	0 (0.0%)	2 (1.8%)
≥60	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
OCCUPATION					
Student	27 (100.0%)	22 (81.5%)	20 (76.9%)	21 (77.8%)	91 (83.5%)
Employed	0 (0.0%)	5 (18.5%)	6 (23.1%)	6 (22.2%)	18 (16.5%)
MEAN†					**Mean Total**
NOISE SENSITIVITY	2.51	3.07	2.82	3.04	2.86
					Total
No. of Participants	**27**	**27**	**28**	**27**	**109**

†Mean self-reported noise sensitivity of the respondents was higher than "Good".

Table 4-5 A summary of the characteristics of the four survey sites

Estate	Sites	Direction	Sky%	Green%	Open area (m^2)	*LAeq*	Function
RHE A	A1	Forward	0	10	301	68	Play area
		Return	18	45	77	69	
	A2	Forward	5	43	106	65	Play area
		Return	20	12	264	64	
	A3	Forward	0	1	122	65	Path area
		Return	21	29	59	65	
	A4	Forward	0	0	45	65	Path area
		Return	2	46	122	66	
	A5	Forward	1	6	249	72	Sit area
		Return	1	18	249	72	
	A6	Forward	0	11	538	70	Path area
		Return	0	10	370	67	
	A7	Forward	2	19	141	67	Play area
		Return	0	2	180	67	

RHE B	B1	Forward	0	17	142	68	Path area
		Return	0	1	71	72	
	B2	Forward	1	8	316	66	Path area
		Return	0	45	453	69	
	B3	Forward	4	67	106	62	Sit area
		Return	8	30	115	63	
	B4	Forward	4	8	283	66	Sit area
		Return	12	60	323	65	
	B5	Forward	3	38	572	65	Play area
		Return	3	12	452	64	
	B6	Forward	0	10	51	64	Path area
		Return	2	23	76	62	
RHE C	C1	Forward	0	19	72	61	Path area
		Return	5	45	57	62	
	C2	Forward	0	13	7	68	Path area
		Return	1	1	9	73	
	C3	Forward	7	26	255	59	Play area
		Return	1	59	109	60	
	C4	Forward	2	30	62	60	Sit area
		Return	8	19	50	59	
	C5	Forward	0	12	23	64	Path area
		Return	1	9	20	67	
	C6	Forward	12	2	120	62	Path area
		Return	2	5	37	64	
	C7	Forward	1	3	325	65	Path area
		Return	1	3	265	63	
	C8	Forward	0	9	329	62	Sit area
		Return	0	20	206	62	
RHE D	D1	Forward	2	11	561	65	Path area
		Return	4	26	343	64	
	D2	Forward	4	20	363	64	Path area
		Return	2	0	277	64	
	D3	Forward	2	28	48	68	Play area
		Return	3	19	42	67	
	D4	Forward	3	44	75	67	Play area
		Return	5	13	82	68	
	D5	Forward	10	42	67	65	Play area
		Return	0	45	121	67	
	D6	Forward	2	63	8	67	Sit area
		Return	0	47	9	69	
	D7	Forward	0	17	471	63	Path area
		Return	12	24	233	64	

4.2.2 Spatiotemporal variability of soundscape in multifunctional areas

A set of sound maps were produced to facilitate visual identification of the variations in soundscape assessments and psychoacoustic parameter values across 4 survey routes during the morning, afternoon and evening sessions. Route in RHE C was selected as an illustrative example due to its distinct representation of both the highest and lowest soundscape rating points.

Figure 4-2 illustrates the distribution of the mean soundscape quality ratings and four different psychoacoustic parameter values of RHE C across different time periods. Soundscape quality ratings were categorized and colour-coded -- low (= SQ<4) in blue, medium (4⩽SQ⩽6) in green and high (SQ>6) in red. Similarly, the colour legends of the psychoacoustics parameters followed the jet colormap, which range from blue to red. Point C3, the only play area in RHE C, received a high soundscape quality rating in the afternoon and evening, and a medium rating in the morning. Situated next to a downhill side and surrounded by extensive vegetation, this play area is enriched with natural sounds such as birdsong, cicada sound and rustling leaves throughout the day, contributing to high sharpness values. Besides the greenery, the area's openness, offering expansive views of sky despite its proximity to two high-rise buildings, enhances its appeal. The sound maps reveal that the fluctuation strength was high in the afternoon and evening, attributed to the activity of children playing. The prominent sounds of children playing contribute to a vibrant and lively atmosphere, leading to higher soundscape quality rating during these periods.

Interestingly, Points C2, C4 and C8 – despite all being located within the same type of functional landscape (i.e., setting-out areas) – received distinctly different soundscape quality ratings. Point C2, situated adjacent to the air-conditioning units of supermarket, was exposed to constant, loud, and harsh noise throughout the day. This disrupted the expected tranquillity of the sitting-out area, resulting in the lowest soundscape quality rating. On the contrary, Point

C4, which was ensconced in abundant greenery, attracted the highest soundscape quality rating. This sitting-out area was surrounded by plenty of greenery, producing medium roughness of rustling leaves sound and attracting high sharpness of birdsong frequently. Point C8 was at an open ground with rest seats and received medium soundscape quality rating. Located at the upper deck with some greenery, this area was relatively peaceful, though light road traffic noise from a trunk road below was occasionally audible.

Most of the circulation areas (Points C1, C5, C6 and C7) received medium soundscape quality ratings except for Points C5 and C6. Point C5, located at a downslope of an escalator, which was a sidewalk of a restricted road adjacent to a covered walkway. Specifically, this busy circulation area was dominated by high fluctuation strength and loudness arising from human sound or extremely loud traffic noises, resulting in low soundscape quality. Point C6 was an elevated entrance plaza adjacent to a kindergarten and main entrance to the estate. Pedestrian sound of high fluctuation strength and traffic noises from the trunk road underneath of high loudness could be heard in the morning rush hours, resulting in low soundscape quality being rated for this time period. In the remaining time periods, this place was less busy and shared the similar sound environment and soundscape quality with Points C1, C7 and C8.

Human sound and machine sound were driven primarily by people activities in different time periods. In comparison, natural sound and road traffic noise were affected by both the local spatial attributes (e.g., greenery rate and presence of cars) and temporal effects (e.g., the activity cycles of animals and the peaks of traffic flow). Results also show that same set of aural attributes seem to play different roles in different types of functional space, such as dominant human sound with high fluctuations (e.g., children playing) enhance the vibrancy in play areas, but decrease the tranquility of sitting-out areas.

To quantify these differences further, prediction models were needed to assess the impacts of various aural and visual landscape elements, openness, and functional space types on soundscape quality. Before developing the model, preliminary bivariate statistical analyses were conducted to identify the key determinants influencing soundscape quality.

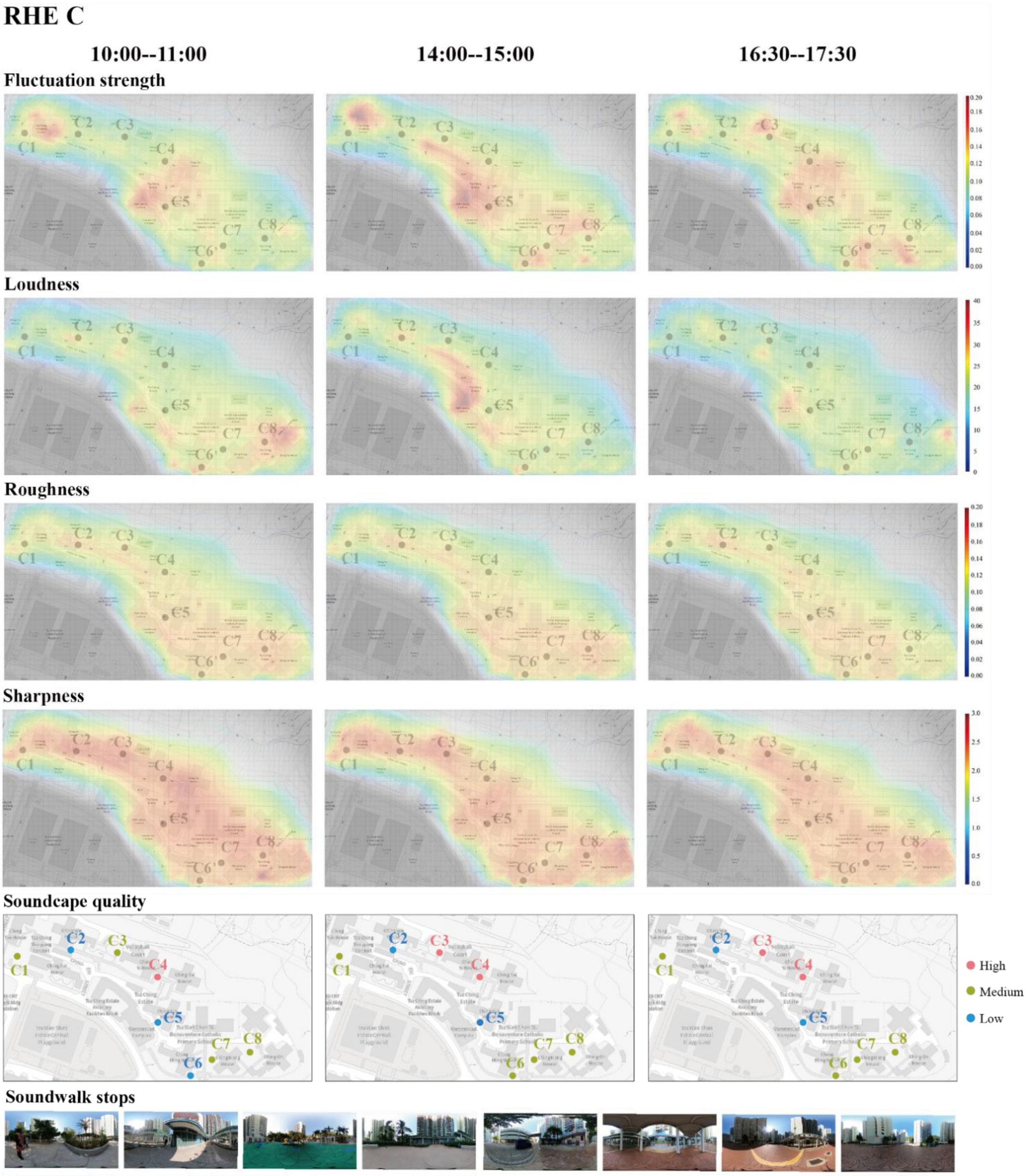


Figure 4-2 Sound maps showing the distribution of psychoacoustic parameter values and mean soundscape quality ratings of RHE C at different time periods

Soundscape quality was found to be negatively correlated with LAeq (r = -0.462, p = 0.001), perception of dominant of road traffic noises (r = -0.247, p = 0.001), perception of dominant of human sounds (r = -0.126, p = 0.001) and perception of dominant of machine sounds (r = -0.199, p = 0.001). On contrary, perceptions of birdsong (r = 0.293, p = 0.001) and rustling leaves (r = 0.273, p = 0.001) were positively correlated with soundscape quality.

By expressing the view proportions of visual attributes in terms of percentages, soundscape quality was found to be positively correlated with percentage of greenery (r = 0.236, p = 0.001), percentage of sky (r = 0.175, p = 0.001) and open space area (r = 0.052, p = 0.044). In addition, greenery percentage was positively correlated with the perceptions of birdsong (r = 0.192, p = 0.001) and rustling leaves (r = 0.168, p = 0.001) as well as the perception of dominant birdsong (r = 0.139, p = 0.001). Greenery percentage (r = -0.109, p = 0.001) and sky percentage (r = -0.079, p = 0.002) were found significantly and negatively correlated with the perception of dominant road traffic. This is not surprising, as both some natural views and sounds have been shown to be effectively reduce the perception of traffic noise and enhance soundscape quality.

Table 4-6 summarizes the aural and visual environmental characteristics of the three types of microscale functional space. Significant differences were observed among them in terms of physical sound and psychoacoustic properties, including LAeq (F=15.490, p=0.001<0.05 by ANOVA), loudness (F=22.054, p=0.001<0.05), fluctuation strength (F=17.297, p=0.001<0.05), Lceq-Laeq (F=5.790, p=0.003<0.05) and LA10-LA90 (F=9.424, p=0.001<0.05). The percentages of sky (F=33.26, p=0.001<0.05 by ANOVA), open area (F=41.303, p=0.001<0.05) and greenery (F=185.38, p=0.001<0.05). Thus, a more detailed examination of aural and visual perception effects on different types of microscale functional space is necessary to gain a better understanding on the soundscape quality assessments in open spaces comprising multifunctional landscape spaces.

Significant differences in mean soundscape quality ratings were observed between play and circulation areas ($\Delta\mu$=-0.99, p=0.001<0.05 by ANOVA with a follow-up Tukey's HSD test), and between sitting-out and circulation areas ($\Delta\mu$=0.70, p=0.001<0.05). However, no significant statistical differences in mean ratings were observed between play areas and sitting-out areas ($\Delta\mu$=0.30, p=0.117>0.05).

Table 4-6 A summary of aural and visual environmental characteristics of three types of microscale functional space

Function	Play area	Sitting-out area	Circulation area
Physical acoustic environment			
LA_{eq}	67.48	65.61	67.97
Loudness	21.42	20.31	22.56
Sharpness	1.43	1.40	1.42
Roughness	0.13	0.13	0.13
Fluctuation strength	0.13	0.11	0.11
L_{ceq}-L_{aeq}	8.34	8.42	8.88
LA_{10}-LA_{90}	5.14	4.39	4.69
Perceived acoustic environment			
Dominant machine sound	6.5%	15.7%	5.6%
Dominant road traffic noise	30.6%	33.7%	57.0%
Dominant human sound	48.6%	23.6%	23.8%
Dominant birdsong	14.3%	27.0%	13.6%
Visual landscape			
Greenery	28.7%	31.4%	13.9%
Visual openness			
Sky	5.1%	3.2%	2.7%
Open area	181m^2	128m^2	216m^2

4.3 Conclusions

Chapter 4 utilized correlation analyses and qualitative evaluations of sound maps to preliminarily investigate the influence of multisensory and multifunctional factors on soundscape quality, laying the foundation for subsequent model development. The findings indicate that soundscape quality is significantly influenced not only by multisensory inputs, including auditory, visual, and thermal factors, but also by functional spaces and their associated activities. This highlights that soundscape evaluation is inherently multidimensional and complex, involving dynamic interactions between sensory integration and activity contexts.

The analysis revealed that natural sounds, such as birdsong, and visual greenery contribute positively to soundscape quality, whereas traffic noise and densely built structures may exert negative impacts. Moreover, activities within functional spaces produce varying effects on soundscape perception depending on their type and intensity. For instance, activities in rest areas may reduce tranquillity, while those in play areas may enhance vibrancy. These findings underscore the importance of considering both multisensory inputs and multifunctional activities in shaping perceived soundscape quality.

Building upon these preliminary findings, Chapter 5 develops a theoretical framework based on structural equation modelling (SEM) to systematically analyze the direct and indirect relationships among key factors and to uncover their roles in soundscape evaluation. Through the expansion and validation of this theoretical framework, the study aims to provide stronger scientific foundations and practical insights for understanding and optimizing soundscape quality in urban open spaces.

Chapter 5 Theoretical framework for soundscape evaluation

5.1 Hypotheses and Conceptual Framework

To further analyze the integrated effects of multidimensional factors on soundscape quality and validate the relationships identified in the preliminary correlation analysis in Chapter 4, this section aims to develop a comprehensive theoretical framework and conceptual model. Table 5-1 lists all the main assumptions employed for developing the conceptual model based on the findings identified from relevant references. The years of review ranged from

1999 to 2024, using keywords "soundscape, landscape, thermal comfort, soundscape descriptors, soundscape indicators, psychoacoustic, outdoor urban spaces and soundscape perceptions". For revealing all the potential relationships for quality of public open space, we have included both the relationships that have been previously confirmed and those have not fully confirmed (i.e., H10, H11, H13, H14, H15 and H18) as our major hypotheses in the model development. In addition, the studied factors have been further categorized according to different types of sensory variables - auditory, visual, and thermal as shown in Table and Fig shown below (Geng et al., 2022; Lau and Choi, 2021; Nitidara et al., 2022). The visual factors include visibility of greenery, road and sky; the auditory factors include perceived dominance of sound sources (e.g., vehicle noise, human sound and birdsong), LAeq, and Psychoacoustic factors (e.g., fluctuation strength and sharpness); the thermal factors like PET, thermal sensation, thermal comfort and thermal acceptability.

Table 5-1 Major hypotheses of the conceptual model

Hypotheses Descriptions	References
Auditory Factors	
H1a: *LAeq* influences Pleasantness	(Axelsson et al., 2010; Jeon and Hong, 2015; Lindborg and Friberg, 2016)
H1b: *LAeq* influences Eventfulness	(Axelsson et al., 2010; Jeon and Hong, 2015; Lindborg and Friberg, 2016)
H2a: Perceived dominance of sound influences Pleasantness	
H2ai: Perceived dominance of traffic sound → **Pleasantness**	(Hasegawa and Lau, 2022; Jeon and Hong, 2015; Jo and Jeon, 2021; Zhao et al., 2021)
H2aii: Perceived dominance of human sound → **Pleasantness**	(Jeon and Hong, 2015; Jo and Jeon, 2021; Zhao et al., 2021)
H2aiii: Perceived dominance of birdsong → **Pleasantness**	(Hasegawa and Lau, 2022; Jeon and Hong, 2015; Jo and Jeon, 2021; Zhao et al., 2021)
H2b: Perceived dominance of sound influences Eventfulness	
H2bi: Perceived dominance of traffic sound → **Eventfulness**	(Hasegawa and Lau, 2022; Jeon and Hong, 2015; Jo and Jeon, 2021; Zhao et al., 2021)

H2bii: Perceived dominance of human sound → **Eventfulness**	(Jeon and Hong, 2015; Jo and Jeon, 2021; Zhao et al., 2021)
H2biii: Perceived dominance of birdsong → **Eventfulness**	(Hasegawa and Lau, 2022; Jeon and Hong, 2015; Jo and Jeon, 2021; Zhao et al., 2021)
H3: Psychoacoustic parameters influence the perceived dominance of sound	(Hasegawa and Lau, 2022; Yang and Kang, 2013)
H4a: Pleasantness influences soundscape quality	(Aletta et al., 2016b; Axelsson, 2015; Hasegawa and Lau, 2022; Hong and Jeon, 2015; Jeon et al., 2018)
H4b: Eventfulness influences soundscape quality	(Aletta et al., 2016b; Axelsson, 2015; Hasegawa and Lau, 2022; Hong and Jeon, 2015; Jeon et al., 2018)
Visual Factors	
H5: Subjective visual dominance influences landscape visual quality	
H5a: Visibility of road → Landscape visual quality	(Hasegawa and Lau, 2022; Jo and Jeon, 2021)
H5b: Visibility of greenery → Landscape visual quality	(Hasegawa and Lau, 2022; Jo and Jeon, 2021)
H5c: Visibility of sky → Landscape visual quality	(Hasegawa and Lau, 2022; Jo and Jeon, 2021)
Thermal factors	
H6: PET influences thermal sensation	(Chan and Chau, 2021; Hoppe, 1999)
H7: Thermal sensation influences thermal comfort	(Chan and Chau, 2021; Hoppe, 1999)
H8: Thermal comfort influences thermal acceptability	(Chan et al., 2017)
Sensory Interactions	
H9: *LAeq* influences thermal comfort	(Jin et al., 2020; Lau and Choi, 2021; Pellerin and Candas, 2003)
H10: Perceived dominance of sound influences thermal sensation*	(Geng et al., 2022; Jin et al., 2020)
H11: Subjective visual dominance influences perceived dominance of sound*	(Jeon and Jo, 2020)
H12: Landscape visual quality influences soundscape quality	(Carles et al., 1999; Jeon and Jo, 2020; Ou et al., 2017)

H13: Thermal acceptability influences soundscape quality*	(Jin et al., 2020; Lau and Choi, 2021; Nitidara et al., 2022)
Others	
H14a: The function of space influences Pleasantness*	(Baran et al., 2014; Hong and Jeon, 2015, 2017a, b; Van Hecke et al., 2016)
H14b: The function of space influences Eventfulness*	(Baran et al., 2014; Hong and Jeon, 2015, 2017a, b; Van Hecke et al., 2016)
H15: The function of space influences psychoacoustic parameters*	(Hong and Jeon, 2017a; Rychtáriková and Vermeir, 2013; Yang and Kang, 2013)
H16: Soundscape quality influences overall open space quality	(Hong and Jeon, 2013; Nilsson et al., 2012; Zhang et al., 2017)
H17: Landscape visual quality influences overall open space quality	(Hong and Jeon, 2013; Nilsson et al., 2012)
H18: Thermal acceptability influences overall open space quality*	(Nitidara et al., 2022)
H19: Self-assessed auditory capacity influences Pleasantness	(Lindborg and Friberg, 2016)

Note:
- The hypothesis shown in italics with * denotes that has not been thoroughly confirmed
- The bolded hypothesis denotes major hypotheses, while the non-bolded one denotes the sub-hypotheses under a specific major hypothesis.
- Abbreviation: PET --- Physiological Equivalent Temperature.

Based upon the above hypotheses, a conceptual model has been proposed in Figure 5-1 to illustrate the interrelationships among soundscape quality, sound environment, visual landscape, and thermal environment, and people's perceptions.

Firstly, soundscape quality refers to the overall perception and evaluation of the acoustic environment in open spaces. It is influenced not only by the perceived affective quality of the soundscape (i.e., Pleasantness and Eventfulness) but also by the visual quality of the landscape and thermal perception, based on the interaction between different sensory modalities (Nitidara et al., 2022).

Secondly, it is hypothesized that the perceived affective quality of the soundscape is affected by the subjective perceived dominance of sound sources and physical sound properties (e.g., $LAeq$, LA_{10}-LA_{90}, LC_{eq}-LA_{eq}). Additionally, the perceived dominance of sound sources is influenced by physical sound properties and psychoacoustic factors (e.g., fluctuation strength (*FS*) and sharpness); It is also hypothesized that landscape visual quality is influenced by the visibility of visual elements; and that thermal perception is related to thermal perceptual factors, which are evaluated by thermal physical factors.

Thirdly, the model proposes interactions between different sensory-related factors, where the visibility of visual elements influences the perceived dominance of sound sources, which in turn affects thermal perceptual factors.

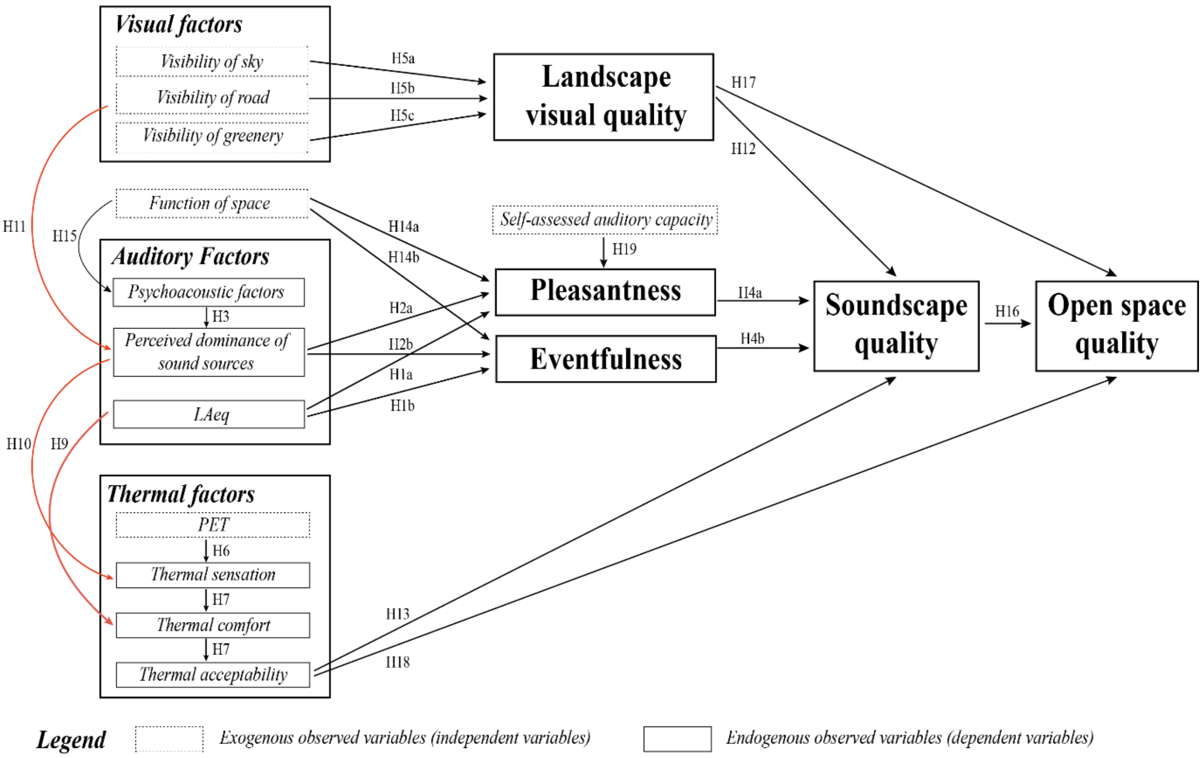


Figure 5-1 The proposed conceptual framework of this study

5.2 Structural equation modelling

In total, 1749 valid responses were successfully administered via face-to-face interviews at the COS of nine PHEs. Each interview lasted for about five to ten minutes on average. The collected subjective human responses and physical field measurement data were statistically analyzed using SPSS version 22.0, while a path model was formulated using AMOS version 22.0.

Given the mild winter weather conditions in Hong Kong between 2021 and 2023, only one path model has been developed based on the 1749 questionnaire responses. These responses were recorded within a narrow-recorded temperature range, with 69% of the survey days exceeding 27 °C. The sample size of 1749 responses are more than adequate for constructing the model, surpassing the minimum recommended sample size of 200 for structural equation modeling and adhering the rule of thumb that requires 10 samples per variable (i.e., 21 variables in this study).

Table 5-2 shows our model results satisfied both the criteria for acceptance values of the goodness-of-fit (GFI) tests and the root mean square error of approximation (RMSEA) frequently used for assessing the GFI of structural equation models, the constructed model is considered a reasonably good representation of the interrelationships.

In addition, the reliability and validity of all the observed variables have been evaluated. Specifically, the Cronbach's alpha values for all observed variables exceeded 0.7, indicating good internal consistency. Furthermore, only the statistically significant path coefficients ($p < 0.05$) have been retained for our model construction, highlighting the robustness and validity of the proposed model. Figure 5-2 shows the constructed path model together with the estimated correlation values for each of individual factors. All coefficient values have been standardized to facilitate comparison. A low coefficient indicates a weak association, while a high coefficient indicates a stronger causal relationship between the independent and dependent variables. A positive coefficient suggests a direct relationship, meaning that as the value of the independent variable increases, so does the value of the dependent variable. Conversely, a negative coefficient indicates an inverse relationship, where an increase in the independent variable leads to a decrease in the dependent variable. A dummy variable (i.e., 'Child_Play areas') has been created for facilitating comparison of the differences among play areas dominated by children's play activities and others.

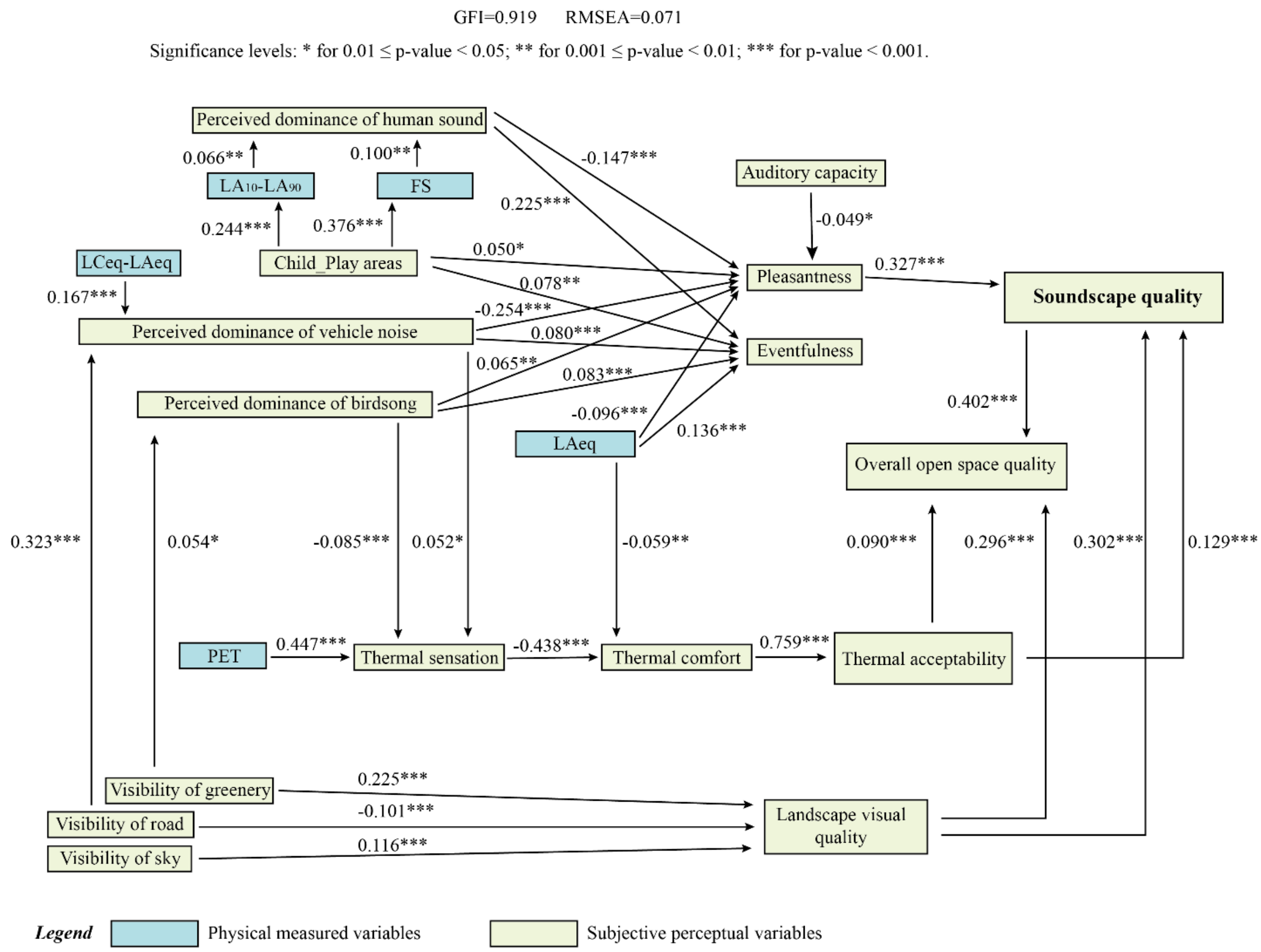


Figure 5-2 The formulated path model displaying the estimated coefficient values for individual factors

Table 5-2 Criteria for acceptance and estimated values of goodness-of-fit index indices of the model

Goodness-of-fit index	Acceptance value	Model value
Goodness-of-fit index (GFI)	>0.9	0.919
Root means square error approx. (RMSEA)	≤0.08	0.071

Table 5-3 shows the direct, indirect and total effects of individual factors on soundscape quality. Soundscape quality was greatly influenced by pleasantness of the sound environment (β = 0.327), landscape visual quality (β = 0.302) and thermal acceptability (β = 0.129).

Pleasantness rating would be slightly increased with perceived dominance rating of birdsong (β = 0.065). Conversely, more factors were found to be exert negative influences on pleasantness ratings. Pleasantness rating would be slightly decreased by a higher LA_{eq} (β = -0.096), but greatly decreased with a higher perceived dominance rating of vehicle noise (β = -0.254), a higher perceived dominance rating of human sounds (β = -0.147), and to a lesser extent auditory capacity (β = -0.049). The perceived dominance rating of vehicle noise was associated with LC_{eq}-LA_{eq}, which is an index used for measuring of relative proportion of low-frequency sounds. Besides, play areas dominated by children would produce sounds of higher fluctuation strength (β = 0.244) and LA_{10}-LA_{90} (β = 0.376) values. Both of them were positively associated with perceived dominance rating of human sounds. Interestingly, play areas dominated by children were directly and positively correlated with pleasantness (β = 0.050). In consequence, play areas dominated by children were found to produce a net positive effect on soundscape quality (β = 0.014).

With aid of Table 5-3 and Figure 5-2, soundscape quality (β = 0.402) was observed to be directly related to open space quality in addition to landscape visual quality (β = 0.296) and thermal acceptability (β = 0.090). In turn, thermal acceptability was determined to be directly influenced by thermal comfort (β = 0.759), which was influenced by both thermal sensation (β = -0.438) and *LAeq* (β = -0.059). Thermal sensation was not only affected by *PET* (β = 0.447), but also perceived dominance of vehicle noise (β = 0.052) and perceived dominance of birdsong (β = -0.085).

Landscape visual quality was positively influenced by visibility of greenery (β = 0.225) and sky (β = 0.116), while it was negatively affected by visibility of road (β = -0.101). The visibility of buildings had no significant effect and was removed from the path model. In addition, visibility of greenery would enhance perceived dominance of birdsong (β = 0.054), indirectly mitigating thermal sensation (β = -0.005) and enhancing Pleasantness (β = 0.004).

Similarly, visibility of road would increase perceived dominance of vehicle noise (β = 0.417), indirectly increasing thermal sensation (β = 0.027) and decreasing Pleasantness (β = -0.082). Above all, our findings basically affirmed our hypotheses that sound, visual and thermal environment evaluation as well as their inter-relationship were also determinants for open space quality.

Table 5-3 Direct, indirect and total effects of individual factors on soundscape quality

Factor	**Direct effect**	**Indirect effect**	**Total effect**
Pleasantness	0.327^{***}	0.000	0.327^{***}
Landscape visual quality	0.302^{***}	0.000	0.302^{***}
Thermal acceptability	0.129^{***}	0.000	0.129^{***}
Perceived dominance of vehicle noise	0.000	-0.085^{***}	-0.085^{***}
Perceived dominance of human sounds	0.000	-0.048^{***}	-0.048^{***}
Perceived dominance of birdsong	0.000	0.025^{**}	0.025^{**}
Visibility of road	0.000	-0.058^{***}	-0.058^{***}
Visibility of greenery	0.000	0.069^{***}	0.069^{***}
Visibility of sky	0.000	0.035^{***}	0.035^{***}
LAeq	0.000	-0.037^{***}	-0.037^{***}
Fluctuation strength	0.000	-0.005^{***}	-0.005^{***}
LCeq-LAeq	0.000	-0.014^{***}	-0.014^{***}
LA_{10}-LA_{90}	0.000	-0.003^{*}	-0.003^{*}
PET	0.000	-0.019^{***}	-0.019^{***}
Child_Playgd	0.000	0.014^{*}	0.014^{*}
Auditory capacity	0.000	-0.016^{*}	-0.016^{*}

Note: - Factors printed in *Italics* represent physical measured variables; Factors printed in normal denote perceptual variables; - Significance levels: * for 0.01 ≤ p-value < 0.05; ** for 0.001 ≤ p-value < 0.01; *** for p-value < 0.001.

5.3 Discussion

With aid of the collected 1749 responses from COS visitors and physical field measurement data, a path model has been successfully formulated to provide a holistic view on how sound environment, visual landscape and thermal environment-based factors, and their associated human perceptual factors link to the assessments of soundscape quality of a COS in

PHEs in Hong Kong. To our knowledge, this is one of few large-scale studies that has formulated a path model based on more than 1700 human perceptual responses and physical microenvironmental data collected within a single study. With such a large number of collected data, the model findings have successfully not only revealed that soundscape quality had positive effects on open space quality, but also revealed the intricate cross-modal interrelationships among the related perceptual and objectively measured aural, visual and thermal based factors in COS. In addition, they also provide a string of valuable insights for residential housing estate designers and planners in formulating strategies that can effectively improve soundscape quality in COS in compact city environments to enhance well-being of their residents. They are discussed in detail as follows.

First, the findings confirmed our hypothesis that the physical sound, visual and thermal environments and their respective perceptions by COS visitors significantly affect the soundscape quality in COS. Pleasantness plays a crucial role in auditory perception, significantly enhancing soundscape quality with the highest relative influence (relative influence =0.327) (Jeon et al., 2018; Pérez-Martínez et al., 2018). This is because pleasantness mirrors an individual's emotional response to sound, which depends not only on the sound's physical properties, but also on how individuals subjectively interpret it within a specific environment context. Consequently, pleasantness emerges as the primary factor driving soundscape quality, surpassing the physical characteristics of sound and underscoring its essential role in soundscape evaluation.

In addition to auditory factors, the visual quality of landscape significantly influences soundscape assessments. Its relative importance is nearly equal to that of pleasantness (relative influence = 0.302). This is unsurprising, given that key soundscape concepts are often intertwined with the landscape, and 80% of human sensory experiences are visual (Jeon and Jo, 2020). Visual cues not only enhance the perception of positive sounds but also reduce sensitivity to unpleasant one, thereby improving overall soundscape quality. Furthermore, the interaction between auditory and visual stimuli shapes an individual's overall assessment of the aural environment, explaining its high relative influence in the model (Jeon and Jo, 2020).

Furthermore, our path model findings suggested that the relative influences of thermal perception on soundscape quality was comparable in order with that of pleasantness or visual landscape quality despite its relative influences being smaller than the latter two (Thermal acceptability vs Pleasantness vs Visual landscape quality: 0.129 vs 0.327 and 0.302). They are in line with the relative weighting of influence of thermal-auditory-visual sensation on overall comfort reported for an open space in the tropical region in Bandung (Thermal Sensation vs Auditory sensation vs Visual sensation: 0.13 vs -0.31 vs 0.30) despite an indirect thermal sensation's influence via aural and visual sensation being reported (Jeon and Jo, 2020). Evidently, our finding on direct thermal influence was affirmed by many multisensory research findings that there exist significant cross-modal interactions between different types of sensory as they are all interconnected in human brain (Calvert, 2001). In addition, cross-modal aural-thermal interactions have been observed in some previous binary sensory studies conducted in open space. For instance, thermal perception was shown to interact directly with auditory perceptions, and high heat stress in summer would directly lead to low acoustic comfort regardless of the variations in the *LAeq* in urban squares located in severe cold Harbin *(Jin et al., 2020)*. In view of importance of perceptual and physical thermal environmental factors, lack of considerations of them in many earlier studies made the soundscape assessment biased and less comprehensive, resulting in sub-optimal strategies in enhancing soundscape quality in COS.

Second, our findings confirmed our hypothesis that pleasantness exerted direct positive influence for soundscape quality. Although such relationships have been reiteratively confirmed for many different types of open spaces such as parks and squares, and also for different cities in different countries, our findings strengthened the existing knowledge by identifying the specific major factors affecting pleasantness as well as revealing their relative influences.

The perception of dominant sound types was found to be a key factor influencing pleasantness in COS. This can be understood through the emotional responses to sounds, as pleasantness represents an emotional magnitude of sound perception (Erfanian et al., 2021; Fan et al., 2015), and emotion is directly associated with sound type (Erfanian et al., 2021). Specifically, pleasantness in COSs can be enhanced by a higher perceived dominance rating of birdsong (β = 0.065), and reduced by a higher perceived dominance rating of road traffic noise (β = -0.254), and human sounds (β = -0.147). This affirms the Axelsson et al.'s findings (Axelsson et al., 2010) that natural sounds have the most positive effects while road traffic sounds have the most negative impacts.

Given the significant impacts of perceived dominance of birdsong, human sounds and road traffic sounds on soundscape quality, it is crucial to implement measures that reduce the perceived dominance of human and road traffic sounds, or enhance the perceived dominance of birdsong. Notably, efforts should be focus on reducing perceived dominance of road traffic sounds as they have the largest impact on soundscape quality among all studied factors (total β = -0.085).

To mitigate unwanted sounds, several strategies can be employed. For instance, installing noise barriers (Hong and Jeon, 2014) with sound-absorptive materials (Yang and Jeon, 2020) near busy traffic roads and implementing traffic flow management (Tan et al., 2022) can lower the intensity of road traffic noise, thereby reducing its perceived dominance. Additionally, introducing pleasant sounds like water sounds and birdsong can help mask road traffic noise (Li et al., 2024; Nilsson and Berglund, 2006). However, the effectiveness of water sounds and birdsong in masking traffic noise varies based on factors such as the type of masking sound (Galbrun and Ali, 2013), specific type of traffic noise (Jeon et al., 2010), location (Nilsson et al., 2010), and the presence of other sound sources (Han et al., 2023). High-frequency birdsong is more effective than low-frequency one (Chau et al., 2023), but its sound pressure level must be controlled to avoid becoming disruptive (Hao et al., 2016). Water sounds are most effective when their sound pressure level is similar but not less than 3 dB below than traffic noise (Jeon et al., 2010; You et al., 2010).

Beyond auditory measures, visual elements like water features, birds, and appealing landscapes can attract visual attention and divert perception away from the dominance of road traffic noise (Yang and Kang, 2005). The perceived dominance of human sounds can be reduced by maintaining crowd density within 0.10-0.52 person/m^2 (Hong and Jeon, 2020), and designating quiet zones (Jo and Jeon, 2020a), Conversely, the dominance of birdsong can be enhanced by introducing greenery to create visual buffers (Jeon and Jo, 2020) and habitats for birds (Lu et al., 2020), as well as deploying active birdsong generating systems (Hong et al., 2021).

Contrary to our hypothesis, eventfulness, often considered as a major perceptual dimension of perceived sound quality, was found not a determinant for soundscape assessments in the surveyed COSs. The relationship between eventfulness and soundscape quality is highly context-dependent, yielding mixed results across different studies. For instance, a study found a positive effect of eventfulness in recreational and commercial areas (Hong and Jeon, 2015), while others reported a negative effect in residential areas (Hasegawa and Lau, 2022), or even non-significant effects in both residential and CBD areas (Hong and Jeon, 2015). In addition, the correlation between eventfulness and overall soundscape quality varied across France, Korea, and Sweden (Jeon et al., 2018). Further analysis of our collected data and path model findings revealed that the screaming and shouting from children’s play activities in play areas significantly elevated the eventfulness ratings, creating a lively and dynamic soundscape that positively enhanced soundscape quality ratings in these areas (Axelsson et al., 2010). However, in sitting-out areas, human conversation tended to increase eventfulness, but might negatively impact soundscape quality. This further confirms that the types of events occurring in a space significantly impact this association (Hong and Jeon, 2015, 2020). Given that eventfulness ratings used for our model construction were based on those from both play areas and sitting-out areas, it is not surprising that overall eventfulness was not associated with soundscape quality.

In comparison, less attention can be given to physical sound properties and psychoacoustics factors as their relative influences on pleasantness were found to be only about one-third of those of aural perceptual factors (total influence = 0.163 vs 0.466). This strengthens earlier notion that physical sound property and psychoacoustics factors play a comparatively lesser role on soundscape perception than perceptual factors (Ricciardi et al., 2015). Despite so, a few physical and psychoacoustic factors were still found in this study to exert some influences on pleasantness and in turn soundscape quality. Elevated overall LA_{eq} levels would produce negative pleasantness ratings (β = -0.096), which aligns with previous findings that consistently link high LA_{eq} levels to poor soundscape quality (Ricciardi et al., 2015). Similarly, high $\mathrm{LC_{EQ}}$-$\mathrm{LA_{EQ}}$ also led to lower pleasantness ratings (β = -0.042). This was probably attributed by high intensities of low-frequency sounds, i.e., LC_{eq}-LA_{eq}, being emanated from sources like urban road noises (Tan et al., 2022). Regarding LA_{10}-LA_{90} and fluctuation strength, both exhibited similar negative effects on pleasantness ratings (with β = -0.010 for LA_{10}-LA_{90} and β = -0.015 for fluctuation strength). These findings align with previous finding on intrusive noises such as screeching brakes, which also had adverse impacts. However, it is interesting to note that high LA_{10}-LA_{90} and fluctuation strength caused by children's screams in play areas had an opposite effect, contributing positively to pleasantness ratings (Aumond et al., 2017; Maristany et al., 2016). This reaffirms that the direction of their influences is context-dependent, varying based on the specific type and context of sound (Aumond et al., 2017; Yang and Kang, 2013).

In view of the foregoing, adopting measures like implementing traffic management on nearby roads (Tan et al., 2022) can contribute to lower overall noise levels (LA_{eq}) in COS. Establishment of green and blue buffer zones can not only reduce noise variability (LA_{10}-LA_{90}) but also mitigate low-frequency noise (LC_{eq}-LA_{eq}) (Yang and Kang, 2013). Additionally, use of sound-absorptive and reflected materials on constructions and landscape settings in open spaces can produce a high-quality soundscape by effectively decreasing both the intensity (LA_{eq}) and fluctuation strength of unwanted sounds (Rychtáriková and Vermeir, 2013).

Third, visual quality of landscape could be altered by visibility of some natural and built features. In addition to confirming previous findings on the positive impact of greenery and/or sky visibility on soundscape assessment (Lugten et al., 2018; Ren et al., 2023; Tan et al., 2022) our study further revealed that greenery visibility was more effective than sky visibility in the context of COS (i.e., the relative influence of greenery (β = 0.069) > sky (β = 0.035)). On the contrary, visibility of road should be avoided or concealed as it would lead to negative assessments through both a direct effect on visual quality (β = 0.031) (Romero et al., 2016; Tan et al., 2022), and an indirect (β = 0.027) visual-aural congruency effect induced by perceived dominance of traffic noise. Similar to those observed in another high-dense city, Singapore (Tan et al., 2022), visibility of buildings was found not to affect soundscape assessment in the environment with densely packed high-rise housing blocks being located in proximity to COS. This is probably attributed to the adaption of people in Hong Kong and Singapore to the adverse effects caused by high-rise buildings in close proximity to their living environment. In short, soundscape quality of COS can be enhanced by providing visibility to greenery and sky, and by reducing visibility of roads and vehicles.

Finally, soundscape quality was found to be directly influenced by thermal acceptability instead of thermal comfort, thermal sensation (Geng et al., 2022; Mohammadzadeh et al., 2023), or PET (Matzarakis et al., 2007) as reported in a number of acoustic comfort studies, as indicated by its higher goodness-of-fit value. Despite the strong correlation between thermal comfort and thermal acceptability, our findings suggest that these concepts are distinct in practice. During the survey, respondents often rated their thermal comfort as moderate while still finding the thermal environment highly acceptable. This implies that thermal acceptability has more flexible criteria than thermal comfort, and respondents generally distinguished between these two psychological states, i.e., satisfaction versus acceptance (Berglund and Gonzalez, 1977; Chan et al., 2017). This helps clarify about whether eliciting perception of thermal comfort, neutrality, or acceptance can directly enhance soundscape quality in open spaces. This finding is particularly significant for open space designers practicing in subtropical hot climates as it is relatively easier for designs to ensure that users feel thermally acceptable rather than comfortable during scorching summer weather.

Notably, thermal acceptability was mainly governed by PET, which is in turn determined by a number of physical micro-environmental factors including air temperature and wind speed and in particular solar irradiation. Conceivably, thermal acceptability can be enhanced by moderating the hot climate conditions through a good open space design, e.g., provision of water ponds, natural or artificial shade, and breezeway (Chan and Chau, 2019). However, it is interesting to observe from the path model that there were also multiple sequences of cross-modal interaction effects which subsequently influenced soundscape quality, i.e., interactions between sound and thermal perception or sensations, followed by interactions between thermal acceptability and soundscape quality. For instance, high LA_{eq} would induce negative effects on thermal comfort and thus soundscape quality (total β = -0.006). High perceived dominance ratings of birdsong would improve soundscape quality indirectly via decreasing thermal sensation (total $\beta = 0.004$). High perceived dominance ratings of vehicle noise would deteriorate soundscape quality via increasing thermal sensation (total $\beta = -0.002$).

5.4 Conclusions

All in all, this chapter added to the existing knowledge by successfully exploring the intricate inter-relationships among multi-sensory human visual, aural and thermal perceptions, built environmental factors and dynamic micro-environmental factors as well as their associations with soundscape quality of COS in residential housing estates in a compact city. In addition, our findings also emphasize the importance of thermal perceptual factors and provide a more holistic understanding of the relative influences of visual, aural and thermal based factors on enhancing soundscape quality of COS in residential housing estates. It is suggested that soundscape quality should better be assessed from multi-sensory perspectives with due consideration of aural, visual and thermal in an integrated manner.

Nonetheless, there are some limitations to our findings. First, it is noteworthy pointing out that our results regarding the relative contributions of auditory, visual and thermal factors may only be applicable to high-dense cities in sub-tropical climate region during hot and mild seasons. Second, we have included all those variables with β values > 0.05 in the model. However, cautions must be exercised in interpreting those with correlations as small as 0.05 or so as they may be simply due to differences highlighted by a large sample size. Third, the applicability of our survey findings to younger demographic groups is relatively limited, as respondents over 60 years old made up a sizable proportion of the total survey population (approximately 35%). Fourth, the structural equation model assumes linear relationships between variables and the absence of significant biases in the data. However, in reality, relationships may be nonlinear or influenced by outliers, potentially affecting model accuracy.

Fifth, our study did not find a significant association between eventfulness and soundscape quality. Cautions should be exercised when interpreting this result as the eventfulness ratings in our path model were derived from a mix of play areas and sitting-out areas, which differ greatly in terms of functional zones and activity types. Future research should explore the potential relationship between eventfulness and soundscape quality across different functional areas, in particular in children's play areas. Finally, further studies should be conducted to explore the potential relationships between personal related factors and soundscape quality as our study only examined self-assessed auditory capacity and perceived affective quality.

Chapter 6 Landscape context and soundscape quality in multifunctional spaces

6.1 Significant impact of landscape contextual factors

Building upon the structural equation model developed in Chapter 5, which systematically explored the complex relationships among multisensory variables and soundscape quality, this chapter shifts focus to examining the specific impacts of landscape contextual factors. While Chapter 5 provided a holistic framework to capture the interactions between auditory, visual, and thermal influences, it is equally important to analyze how spatial and functional attributes of landscapes further shape soundscape perceptions. To achieve this, an o-logit regression model was constructed to quantify the effects of key landscape contextual factors—such as greenery, function, and openness—on soundscape quality based on the soundwalk study. This approach not only identifies the relative importance of these factors but also evaluates their direct and indirect influences through interactions with other sensory variables. By integrating ordinal logistic regression, this chapter deepens the understanding of how landscape design elements influence soundscape quality in multifunctional open spaces.

6.2 O-Logit model

To reveal the influences of individual landscape contextual variables, an empirical multivariate model was developed to predict the soundscape quality using both subjective responses and physical measurement data collected from individual soundwalk stops. In addition, the multivariate model facilitates comparison of influences of a set of factors under the same set of conditions, a task that is challenging with bivariate analysis. Prior to model formulation, the responses given by individual participants at different locations and directions of individual routes during different periods have been treated as separate input data sets. It is assumed that the aural and visual characteristics of soundwalk routes between the survey spots would not affect people's soundscape evaluation of individual survey spots.

In handling the collected participants' responses and physical measurement data, O-logit model form was utilised, as it is well-suited for handling the dependent variables rated on ordinal scales. Its functional form is shown as follows:

$$Y_i = logitP_i(\bar{\boldsymbol{X}}) = \alpha + \sum_{i=1}^{k} \beta_i \bar{\boldsymbol{X}}_{\boldsymbol{i}} + \sum_{i,j} \beta_{i,j} \bar{\boldsymbol{X}}_{\boldsymbol{i}} \bar{\boldsymbol{X}}_{\boldsymbol{j}} + \varepsilon_i$$

(3)

Where $logitP_i(\bar{\boldsymbol{X}})$ represents the logistic probability function, Y_i is dependent variable and X_is are independent variables, β_i area the coefficients associated with X_i, and ε_i is the error term.

The sign of coefficient in front of $\bar{X}_i$ indicates the directional relationship between the Y_i and $\bar{X}_i$. A positive sign suggests Y_i increases with $\bar{X}_i$ and vice versa. Conversely, a negative sign suggests Y_i increases as $\bar{X}_i$ decreases and vice versa. Given we hypothesized that there were interaction effects between specific type of activities or events and type of microscale function of space, we would like to test our whether the interactions between $\bar{X}_i$ $\bar{X}_j$ are significant. The coefficient value $\beta_i$reflects the size of strength of $\bar{X}_i$, and the ratio of the coefficient values of two $\bar{X}_i$s indicates their relative strength. By constructing the O-logit regression model, this study aims to identify the relative effects of independent variables on the dependent variable and analyze their relationships and implications. The magnitude of the coefficients reflects the strength of the effects, and standardized coefficients facilitate the comparison of variable importance, quantifying their contributions and providing clear insights into the model results.

As a result, 1528 sets of response data were used to formulate an O-logit model. To facilitate model formulation, the soundscape quality ratings originally rated on an 11-point scale were re-categorized into three levels, namely low (= SQ<4), medium (4≤SQ≤6) and high (SQ>6), in the final model development.

The final O-logit model form is given by:

$$Y_i = \alpha + \beta_{LAeq}LAeq + \beta_{Bird}Bird + \beta_{Leaves}Leaves + \beta_{Dom_{RTN}}Dom_{RTN} + \beta_{Dom_{HS}}Dom_{HS} + \beta_{Dom_{MS}}Dom_{MS} + \beta_{Open\_Area}Open\_Area + \beta_{Sky}Sky + \beta_{Green}Green + \beta_{Playgd}Playgd + \beta_{Sit}Sit + \beta_{Sit\ x\ Leaves}Sit\ x\ Leaves + \beta_{Sit\ x\ Dom\_MS}Sit\ x\ Dom\_MS + \beta_{Playgd\ x\ Dom_{HS}}Playgd\ x\ Dom\_HS + \varepsilon_i \quad (4)$$

where Y_i represents latent continuous response representing the levels of soundscape quality, and high soundscape quality (*SQ>6*) was the main focus of this study. β_k corresponds coefficients of independent variable $\overline{\boldsymbol{X}}_{\boldsymbol{ki}}$. Table 6-1 summarizes the independent variables of this model.

Table 6-1 Definition and coding of the individual variables in the o-logit model

Variable	Definition	Unit
Aural attributes		
LA_{eq}	A-weighted sound level	1 dBA
Bird	Perception of birdsong. Coded as “1” if the participant could perceive birdsong, otherwise “0”	N/A
Leaves	Perception of sound of rustling leaves. Coded as “1” if the participant could perceive the sound of rustling leaves, otherwise “0”	N/A
Dom_RTN	Perceived dominance of road traffic noises. Coded as “1” if the participant perceived road traffic noises as dominant sound, otherwise “0”	N/A
Dom_HS	Perceived dominance of human sounds. Coded as “1” if the participant perceived human sounds as dominant sound, otherwise “0”	N/A
Dom_MS	Perceived dominance of machine sounds. Coded as “1” if the participant perceived machine sounds as dominant sound, otherwise “0”	N/A
Visual landscape attributes		
Green	Percentage of greenery view	1%
Visual openness attribute		
Sky	Percentage of sky view	1%

Open area	A clearly visible area of space located within the closed boundaries formed by buildings and other obstructions	m^2
Functional space attributes		
Playgd	*Play area. Coded as "1" if the type of functional space is play area, otherwise "0"*	N/A
Sit	*Sitting-out area. Coded as "1" if the type of functional space is sitting-out area, otherwise "0"*	N/A
Other contextual attributes		
*Sit*Leaves*	An interaction term between sitting-out area and rustling leaves	N/A
*Sit*Dom_MS*	An interaction term between sitting-out area and dominant machine sounds	N/A
*Playgd*Dom_HS*	An interaction term between play area and dominant human sounds	N/A

The McFadden's ρ^2 value of the constructed model was 0.220, suggesting an excellent goodness-of-fit of the model for the collected responses (cf. McFadden's ρ^2 value of 0.2-0.4 is analogous to a range of values between 0.7 and 0.9 in R^2 value for a linear regression model). Table 4 below lists the estimated values of non-standardized and standardized coefficient of all the statistically significant variables.

Table 6-2 O-logit Model fitting information

Model fitting information				
Number of groups: responses				1528
Log likelihood at convergence				-1206.0144
McFadden's ρ^2				0.22
Attribute	**Non-Standardized *B***	**Standardized *β***	***p*-value**	**Odds ratio**
Aural attributes				
Sound Pressure Level (*LAeq*)	-0.208	-0.347	0.000	0.812
Birdsong (*Bird*)	0.391	0.082	0.001	1.479

Rustling leaves (*Leaves*)	0.58	0.092	0.000	1.785
Dominant road traffic noise (*Dom_RTN*)	-1.649	-0.345	0.000	0.192
Dominant human sound (*Dom_HS*)	-1.366	-0.262	0.000	0.255
Dominant machine sound (*Dom_MS*)	-1.662	-0.191	0.000	0.19
Visual landscape attributes				
Percentage of green (*Green*)	0.008	0.061	0.019	1.008
Visual openness attributes				
Percentage of sky (*Sky*)	0.036	0.076	0.002	1.037
Open area (*Open_area*)	0.001	0.072	0.002	1.001
Functional space attributes				
Playgd	0.418	0.079	0.014	1.519
Sit	0.419	0.075	0.008	1.521
Other contextual attributes				
Sit *x* Leaves	0.812	0.057	0.034	2.252
Sit *x* Dom_MS	-0.963	-0.076	0.022	0.382
Playgd *x* Dom_HS	1.039	0.149	0.000	2.826
Cut 1	-15.11			
Cut 2	-11.726			

Notably, 22% of the total contribution could be explained by functional space type and other contextual attributes. Functional space types had a significant impact on soundscape quality, with play areas and sitting-out areas each accounting for 4% of the higher soundscape quality evaluations. Compared to circulation area, both play (β_{std} = 0.079) and sitting-out areas (β_{std} = 0.075) had higher soundscape quality. However, it is interesting to note that the assessment of soundscape quality of distinct type of functional space was significantly altered when certain types of sound were heard at certain periods (p-value < 0.05). The perception of rustling leaves further improved the soundscape quality of sitting-out areas (β_{std} = 0.057). The perception of dominant human sounds in play areas greatly enhanced the soundscape quality although human sounds generally led to poor soundscape quality (β_{std} = 0.149). In contrast, the perception of dominant machine sounds significantly deteriorated the soundscape quality of sitting-out area (β_{std} = -0.076).

Visual landscape and openness attributes accounted for 11% of high soundscape quality evaluations, with visual landscape and visual openness contributing 3% (0.061/1.964) and 8% (0.148/1.964) respectively. Overall, visual openness had a positive effect on soundscape quality, i.e., a higher sky view percentage and a larger open area surrounding the observer significantly enhanced soundscape quality. In comparison, percentage of greenery (β_{std} = 0.061) had a slightly smaller effect size than sky view percentage (β_{std} = 0.076) or size of open area directly (β_{std} = 0.072) around the observer, while the latter two had similar positive effect size.

Compared to aural attributes, which could help explain about 67% (1.319/1.964) of high soundscape quality evaluation, visual landscape and openness attributes had lesser impacts. More specifically, the visual openness attributes, including sky view percentage (β_{std} = 0.076) and open area (β_{std} = 0.072), as well as the functional space attributes (β_{std_Playgd} = 0.079 and β_{std_Sit} = 0.075), demonstrated similar positive effects to perceptions of birdsong (β_{std} = 0.082) and rustling leaves (β_{std} = 0.092). However, these positive influences were far smaller than the negative impacts caused by unwanted sounds such as dominant road traffic noise (β_{std} = -0.345), dominant human sound (β_{std} = -0.262), dominant machine sound (β_{std} = -0.191) and sound pressure level (β_{std} = -0.347). Notably, while other contextual attributes, such as the perception of rustling leaves (β_{std} = 0.057) and dominant machine sound (β_{std} = -0.076) in sitting out areas, had relatively minor effects compared to aural attributes, the perception of dominant human sounds in play areas (β_{std} = 0.149 exhibited a significantly larger positive influence, comparable to the negative impact of dominant machine sounds (β_{std} = -0.191).

6.3 Discussion

Considerable variations in soundscape quality rating at individual stops were attributed to differences in sound source type and sound intensities, along with variations in landscape features and spatial geometry. Landscape features including the presence of both natural and artificial landscape features contribute to these variations. For example, areas with abundant greenery provides better habitats and food sources for birds, which can lead to increased diversity of birdsong in those areas (Hong and Jeon, 2017b). Similarly, the proximity and presence of roads within these spaces can lead to increased vehicle noise from cars that are either moving or stationary (Liu et al., 2014a). In addition, landscape spatial geometry, such as elevated terraces, sunken plazas and covered walkways affect sound intensities.

Significant variations in soundscape quality ratings across all the survey stops facilitated the successful development of an ordered logistic model capable of predicting the likelihood of high soundscape quality evaluations for multifunctional open spaces. This model effectively reveals the impacts of landscape contextual factors, including microscale functional space, ongoing activities and events, and visual openness attributes. The insights gained from this model findings contribute to the creation of effective landscape design guidelines aimed at enhancing soundscape quality in multifunctional public open spaces within densely populated cities. These guidelines are going to be discussed immediately as follows:

First, the influence of microscale functional space type on soundscape quality is profound, significantly altering perceptions and evaluation based on sound type and its alignment with the space's intended function. The study reveals that these factors together account for 22% of the high soundscape quality evaluations. Significant variations in soundscape impacts were observed among sitting-out areas, play areas, and circulation areas. Specifically, play areas and sitting-out areas increased the likelihood of receiving higher soundscape quality ratings by approximately 50% compared to circulation areas.

In addition, the perception of specific sounds in a particular type of microscale functional area significantly was found to significantly alter the soundscape evaluation. This implicitly confirms our hypothesis that specific type of activities or events taking place in microscale functional area would significantly alter the soundscape evaluation, as specific types of sounds were considered as proxies for these activities or events. The perception of dominant human sounds, like children playing in play areas, significantly increased the likelihood of a higher sound quality rating by 182.6%. Similarly, the sound of rustling leaves in sitting-out areas enhanced the odds of a higher sound quality rating by 125.2%. In contrast, dominant machine sounds in sitting-out areas remarkably reduced their tranquility, decreasing the likelihood of a higher sound quality rating by 61.8%. These findings underscore that soundscape quality ratings are heavily influenced by the appropriateness of sound types to the functional intent of the area (Hong and Jeon, 2015) and the harmonious relationship between the landscape and soundscape (Jo and Jeon, 2020a). The soundscape quality of play areas significantly improved when survey participants heard sounds of children playing, despite human sound having a negative impact on other types of functional spaces (Brown et al., 2011). Dominant human sounds in play areas enhanced the atmosphere, making it livelier and more vibrant. Similarly, the pleasant sound of rustling leaves positively amplified the ambiance in sitting-out areas, whereas the intrusive noise from machinery had a more pronounced negative impact in these same spaces.

Contrary to our initial assumption that the soundscape quality, perception of sound sources and psychoacoustic properties of a particular microscale functional area within an open space would remain consistent, we found that these characteristics varied significantly throughout the day as indicated by the sound maps and O-Logit model results. Our findings suggest that the influence of daily temporal landscape effects extends beyond specific time intervals or sessions, such as morning, afternoon, or evening. Instead, they should be analysed in relation to the occurrence of specific sound events (e.g., ongoing activities) within each distinct type of functional space. For example, soundscape quality typically correlates with specific patterns such as human activity (Liu et al., 2013b), vehicle flow rhythms, or natural rhythms of the environment (Terleph et al., 2008) occurring within particular types of functional landscape. Notably, certain natural sounds, road vehicle noises, human activities, birdsongs, and even machine sounds exhibit more consistent daily temporal patterns (Terleph et al., 2008). For instance, birdsongs are typically more intense during early mornings and dusk (Liu et al., 2013b), while rush hours are marked by higher traffic noise levels from heavy vehicle flows. Machine sounds often emanate from supermarket air-conditioning units during operational hours. Children's play activities, frequently occurring in afternoons and evenings after school. Sporadic noises from open space or nearby building improvements in the mornings and afternoons. Overall, soundscape quality in different functional spaces is influenced not only by the type of space itself but also by the regular patterns of daily activities.

Second, our findings confirmed the hypothesis that visual openness significantly influences the overall soundscape assessment, accounting for approximately 8% of the total impact. Specifically, attributes of visual openness had a greater effect than greenery, with standardized beta coefficients of 0.148 compared to 0.061 (β_{std} = 0.148 vs 0.061), respectively. This finding contrasts with earlier soundscape literature, where greenery has often been highlighted as a key visible feature (Pheasant et al., 2010; Zhao et al., 2023). It is important to note that the influence of the visual landscape may have been underestimated in this study, as sky view was classified as one attribute of visual openness. Upon closer examination, both the size of the open area directly surrounding an observer and the percentage of open sky demonstrated a similar positive effect size (β_{std} = 0.076 vs 0.072, respectively), slightly exceeding the impact of greenery view (β_{std} = 0.061). Specifically, the likelihood of rating the soundscape quality higher increase by approximately 1% for every additional 10m^2 of open area and by 3.7% for each 1% increase in sky visibility. Conversely, each 1% increase in proportion of greenery view boosts the odds by only 0.8%. These findings suggest that densely populated urban areas, a broad visual field is a more influential than the presence of green spaces, contrasting with Zhao et al.'s research, which highlighted greening as the most crucial non-aural factor. This difference is likely because visual openness significantly enhances soundscape perception by aligning auditory experiences with visual expectations (Hasegawa et al., 2022; Jeon et al., 2013; Smyrnova and Kang, 2010). In locations with expansive views, pleasant sounds such as wind and birdsong are more distinctly perceived, which captures attention and enriches the overall soundscape experience. On the contrary, when physical features are placed in close proximity, significantly reducing the open area around, feelings of oppressiveness and fear (Asgarzadeh et al., 2014; Chung et al., 2022) can be evoked in the observer. This phenomenon may be attributed to the psychological impacts of obstructed views, as suggested by the psychological prospect theory (Ruddell and Hammitt, 1987). In enclosed or cluttered spaces, visual oppression and environmental constraints increase individuals' sensitivity to surrounding noise, which may be perceived as more intrusive and unpleasant, thus negatively impacting their soundscape perception (Hasegawa et al., 2022).

Lastly, this chapter compared the relative contributions and mechanisms of landscape contextual factors in comparison to aural and visual factors in soundscape quality evaluations, highlighting significant differences in their influence patterns and their implications for improvement strategies. Aural factors played a dominant role (Hall et al., 2013; Ricciardi et al., 2015), primarily driven by the strong negative impacts of unwanted sounds such as road traffic (You et al., 2010), human sound (Pijanowski et al., 2011) and mechanical noise (Ma et al., 2021). These sounds significantly decrease soundscape quality, underscoring the priority of addressing noise pollution in urban environments. Meanwhile, the positive effects of natural sounds, such as birdsong and rustling leaves (Song et al., 2018; Zhao et al., 2020), were relatively minor and insufficient to counterbalance the negative effects of noise ($\beta_{std\text{-}Mean}$ = 0.087 vs -0.266). This asymmetry highlights the critical importance of noise control while also suggesting that relying solely on improving auditory environments may not achieve optimal results. In contrast, landscape contextual factors made smaller but important supplementary contributions. Visual openness, including sky view and open area size, enhanced overall environmental perception and psychological comfort by creating a greater sense of openness (Ozdemir, 2010). Functional space design further amplified this effect: when spatial function aligned with the sound type, soundscape quality improved significantly. For example, the presence of human sounds, such as children's playing sound, in play areas matched the functional attributes of the space, enhancing its vibrancy and attractiveness (Lin et al., 2025). Conversely, when the sound type conflicted with the functional space—such as mechanical noise in sitting-out areas—the negative impact was magnified, substantially lowering soundscape quality. This comparison reveals distinct roles for different factors in soundscape quality evaluations: aural factors dominate the direct perception of soundscapes, while landscape contextual factors indirectly enhance soundscape experiences by improving spatial congruence and psychological comfort (Liu et al., 2013a; Pijanowski, 2011). Particularly in high-density urban open spaces, visual openness not only reduces sensitivity to noise but also amplifies the effects of positive auditory elements, contributing to a more balanced soundscape environment.

Based on these findings, this chapter proposes a set of integrated strategies to effectively enhance soundscape quality. First, controlling unwanted sounds such as road traffic and mechanical noise should be prioritized through interventions like noise barriers (Hong and Jeon, 2014) and optimized traffic planning (Tan et al., 2022) to reduce auditory disturbances in urban environments. Second, enhancing visual openness by increasing sky view percentages and open area in open space design can create a greater sense of spaciousness, improving psychological comfort and the perception of positive auditory elements (Zhang et al., 2021). Additionally, optimizing the alignment between functional space and sound type is crucial. Urban planning should carefully consider the intended use of functional spaces and the likely sound types they accommodate; for example, designing more vibrant soundscapes for play areas while minimizing disruptive mechanical noise in tranquil spaces like sitting-out areas. Finally, adopting a holistic design approach that integrates auditory and visual environments can leverage the strengths of visual openness and functional space attributes to compensate for auditory shortcomings, ultimately achieving an overall improvement in both soundscape and landscape quality.

6.4 Conclusions

Above all, this chapter recognizes the critical role of landscape contextual factors in shaping the acoustic environment and investigates their influence on soundscape quality in urban settings. The empirical model, which combines physical sound measurement data with human perceptual data, helps uncover the intricate linkage between various contextual factors and soundscape of a multifunctional open space in a high-dense city – Hong Kong. Our empirical evidence suggests that functional space type attributes, ongoing activities (mediated by their interaction with specific sound types), and visual openness play a significant role in shaping high soundscape quality evaluations. Although aural factors dominate soundscape perception, landscape contextual factors provide critical supplementary benefits. This complementary role helps balance the asymmetry between the stronger negative impacts of unwanted sounds and the relatively weaker positive effects of natural sounds. This role is particularly pronounced when functional spaces align with specific sound types, significantly improving the soundscape experience. The findings emphasize the importance of integrating functional space design, visual openness, and sound source management to enhance soundscape quality in high-density urban areas.

However, there are a few limitations on the applicability of our findings in this study. First, the validity of our findings may not be applicable to middle aged or senior adults as most of our participants were mostly young students recruited from the university campus. Second, this study was conducted in high dense cities, where the types of sound sources and landscapes of open spaces are quite different from low dense cities. Finally, some effects of audio-visual interaction have not been fully captured in the models, despite previous studies suggesting its importance. Despite these limitations, the results of this study should provide valuable insights on how to improve the soundscape quality of multifunctional open spaces in high-dense cities through landscape design.

Chapter 7 Nonlinear effects and multisensory interactions in soundscape quality

7.1 Significant impact of nonlinear effects and multisensory interactions

Chapter 6 employed an ordinal logistic regression model to analyze the significant impacts of landscape contextual factors on soundscape quality, laying a foundation for understanding the multidimensional determinants of soundscape evaluation. However, as a multisensory concept, soundscape assessment involves interactions among auditory, visual, and thermal perceptions, further influenced by sensory integration effects and perceptual thresholds. These complex characteristics often lead to nonlinear variations in soundscape quality, making it difficult for traditional linear models to fully capture and explain such intricate relationships. Base on the dataset of questionnaire surveys and on-site measurements, Chapter 7 aims to further expand the theoretical framework proposed in Chapter 5 by developing a flexible and precise predictive model using machine learning techniques. This chapter focuses on quantifying the nonlinear effects and marginal influences of key determinants on soundscape quality. By adopting more advanced modeling approaches, it not only seeks to improve prediction accuracy and interpretability but also aims to uncover the mechanisms underlying multisensory interactions, providing both theoretical insights and practical guidance for optimizing soundscape design in urban open spaces.

The modeling process consists of several critical steps, including data collection, feature engineering, model training, and result interpretation. First, data were collected through questionnaire surveys and field measurements, forming a robust empirical foundation for model development. Next, feature engineering was applied to extract key variables, ensuring that the model effectively captured essential patterns within the dataset. For the modeling phase, the study employed the XGBoost algorithm, followed by hyperparameter optimization to enhance predictive performance. After training the model, SHAP values were utilized to interpret the results, revealing the relative importance and influence of each variable on the predictions. This process not only improves model transparency but also provides interpretable insights into the factors shaping soundscape quality. Figure 7-1 illustrates the complete modeling workflow, highlighting the sequence from data preprocessing and model construction to result interpretation. By integrating theoretical and empirical analyses, this chapter offers a more comprehensive understanding of multisensory interactions and delivers actionable recommendations for optimizing urban open spaces through soundscape design.

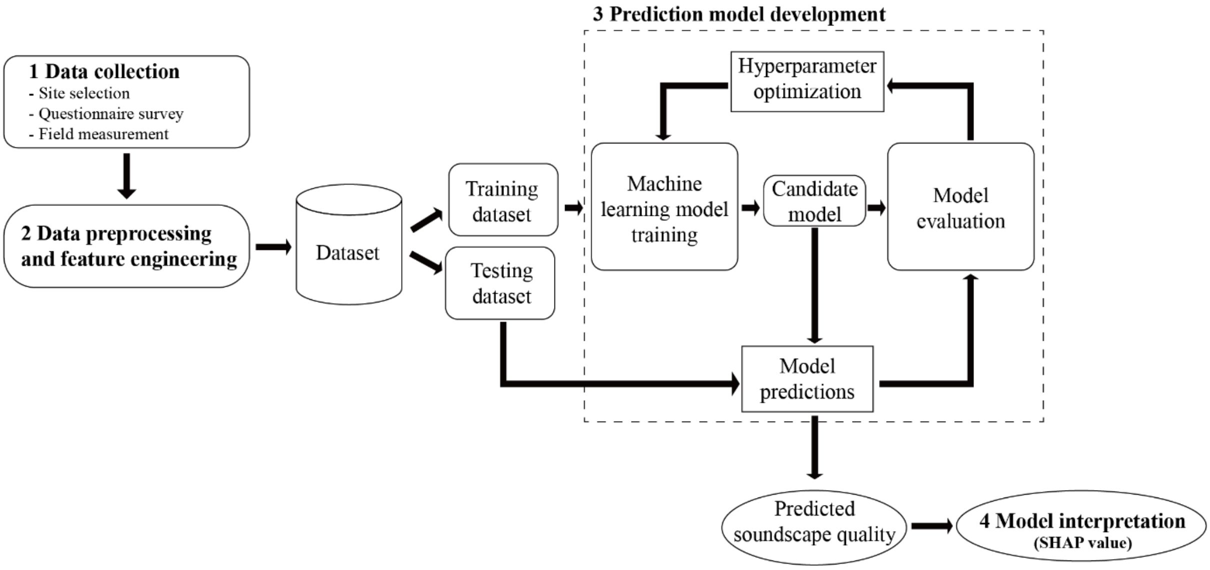


Figure 7-1 The proposed flowchart showing the methodology adopted in this study

7.2 Machine learning model

7.2.1 Data preprocessing and feature engineering

To develop a machine-learning model that can help predict the soundscape quality, a list of physical environmental parameters, respondents' subjective perception of environment and personal characteristics were required to be entered as input features (factors are known as features in machine-learning model development). During the data preprocessing stage, samples with excessive missing values and extreme outliers were removed to ensure data quality and model robustness. After data preprocessing, feature engineering was conducted to identify and retain only the most relevant features for model training. During the feature selection process, subjective visual perception features (e.g., greenery and sky) were removed and replaced with objective percentage values derived from semantic segmentation, minimizing feature redundancy in the regression model. Table 7-1 lists all the input features of model.

Table 7-1 Definition and abbreviation of features

Features	**Abbreviation**	**Definition**
LA_{eq}	*LA*	Equivalent Continuous Sound Pressure Level in A-weighted
Sharpness	*S*	Perception of the high-frequency content of a sound
Roughness	*R*	Hearing sensation for fast modulation frequencies within 20 to 300 Hz
Fluctuation strength	*Fls*	Hearing sensation for modulation frequencies below 20 Hz
LC_{eq} - LA_{eq}	*LC-LA*	Difference between LC_{eq} and LA_{eq}
Hue_Std	*Hue_S*	Standard deviation of hue in view of the respondent
People_count	*People*	Number of people in view of the respondent
Car_count	*Car*	Number of cars in view of the respondent
Green%	*Green%*	Proportion of greenery in view of the respondent
Sky%	*Sky%*	Proportion of sky in view of the respondent
PET	*PET*	Physiological Equivalent Temperature of respondent
Road traffic noise	*RTN*	Perceived dominance of road traffic noise
Rail_sound	*Rail*	Perceived dominance of rail sound
Human_sound	*Human*	Perceived dominance of human sound
Birdsong	*Bird*	Perceived dominance of birdsong
Rustling_leaves	*Leaves*	Perceived dominance of rustling leaves
Building	*Building*	Visual perception of building
Age	*Age*	Age of the respondent
Noise sensitivity	*NS*	Noise sensitivity of the respondent
Health	*Health*	Health condition of the respondent

7.2.2 Prediction model development

This study employed machine-learning techniques using eXtreme Gradient Boosting (XGBoost) and Random Forest (RF) learning algorithms to create prediction models and compared their prediction performance. Additionally, a multiple linear regression model was also constructed for verifying the presumption that machine-learning models offer superior prediction performance compared to traditional multiple linear regression models.

XGBoost (eXtreme Gradient Boosting), which was initially proposed by Tianqi Chen in 2016, represents an advanced and highly scalable implementation of gradient boosting machines (Chen and Guestrin, 2016). In its essence, boosting enhances the overall model prediction accuracy by focusing on excluding weak regressors or classifiers into the formulated models and subsequently consolidating their predictions in a progressive manner to create a robust classifier. To counteract the risk of overfitting, the XGBoost algorithm introduces a regularization term into its objective function, which can be described by:

$$F_{obj} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{k} \Omega(f_k) \quad (4)$$

Where, n is the sample size of training model; $l(y_i, \hat{y}_i)$ is the loss function that represents the model's bias, which is used to calculate the difference between the predicted ($\hat{y}_i$) and true values (y_i) of the model; Ω is the regularization term, which is described below:

$$\Omega(f) = \gamma \mathrm{T} + \frac{1}{2}\lambda\|\omega\|^2 \quad (5)$$

Where γ controls the number of leaf nodes; T represents the number of leaf nodes; λ control the scores in leaves; ω represents the score of leaf nodes.

Random Forest (RF), introduced by Breiman in 2001 [36], is a powerful ensemble learning method that constructs multiple decision trees during training and aggregates their outputs to enhance prediction accuracy and reduce variance. The RF algorithm is based on the Bagging (Bootstrap Aggregating) framework, which generates diverse training datasets by random sampling with replacement. These datasets are then used to build multiple decision trees, each trained on a random subset of features, ensuring low correlation among the trees. The final prediction for regression tasks is obtained by averaging the outputs of all individual trees, as expressed in the following formula:

$$\hat{f}_{RF}^{C} = \frac{1}{C}\sum_{i=1}^{C} T_i(x) \quad (6)$$

Where, C represents the total number of decision trees, $T_i(x)$ denotes the prediction from the i-th tree, and x is the input feature vector. This averaging mechanism helps mitigate overfitting and provides robust performance even with noisy data or high-dimensional feature spaces.

Multi Linear Regression (MLR) is a fundamental statistical modeling technique used to describe the linear relationship between one dependent variable and multiple independent variables. The model assumes that the dependent variables, along with an intercept term and an error term to account for unexplained variance. The general form of the MLR equation is:

$$Y_i = \beta_0 + \sum_{i=1}^{n} \beta_i \bar{\boldsymbol{X}}_{\boldsymbol{i}} + \varepsilon_i \tag{7}$$

Where, Y_i is dependent variable and X_is are independent variables, β_0 is the intercept term, β_i is the coefficient associated with X_i, and ε_i is the error term.

Due to limited context, only the details of the machine-learning models are presented in the following sections.

Hyperparameters, which are the external configurable parameters of a machine-learning model set prior to training process, govern the behavior of training algorithm and directly influence the performance of the model they produce. While traditional methods for finding optimal hyperparameter combinations like grid search and random search are straightforward and have been widely employed, they are computationally demanding and inefficient. Accordingly, this study advances the optimization process by employing Bayesian optimization in tandem with 10-fold cross-validation to refine the hyperparameters of the machine-learning algorithms meticulously. In this process, the data set was randomly divided into 10 subsets, each subset took turns as a validation set to evaluate model performance, while the other 9 subsets were merged together for model training. This optimization strategy was implemented using the Optuna framework, which intelligently adjusts the hyperparameters and leverages of past trial results to predictive model and explore the parameter space. Table 7-2 below shows the range of search space for features (e.g., max_depth) and the model performance evaluated using the root mean squared error (RMSE) as the criterion for optimization.

Table 7-2 The definition and range of search space of hyperparameters

Hyperparameters	Definition	Ranges
Max_depth	Controls tree's depth	3-10 (Both)
Learning_rate	Affects step size in learning	0.01-0.3 (XGBoost)
N_estimators	Sets the number of trees	10-300 (Both)
Subsample	Sample ratio for tree building	0.1-1 (XGBoost)
Colsample_bytree	Decides the feature subset ratio	0.3-1 (XGBoost), None (RF)
Reg_alpha	L1 regularization	0-1 (XGBoost)
Reg_lambda	L2 regularization	0-1 (XGBoost)
Gamma	defines the minimum loss reduction for splits	0-5 (XGBoost)
Min_child_weight	Sets minimum instance weight for child node creation	1-10 (XGBoost)
Max_features	Number of features to consider for splits	0.3-1 or 'sqrt'/'log2' (RF)
Min_samples_split	Minimum samples required to split an internal node	2-10 (RF)
Min_samples_leaf	Minimum samples required to be at a leaf node	1-10 (RF)
Bootstrap	Whether to use bootstrap samples when building trees	True/False (RF)

7.2.3 SHAP Value for Model Interpretation

Despite possessing strong predictive performance, machine-learning models generally suffer from a major drawback that they resemble black boxes lacking of clear interpretability. In order to overcome this drawback, SHAP (SHapley Additive exPlanations) (Lundberg and Lee, 2017) was introduced in this study for offering a unified and mathematically grounded approach to estimate the contribution of each feature to a model's output prediction, thereby enhancing interpretability of black box. Unlike traditional linear regression models, which use the coefficients of independent variables to determine the expected change in the dependent variable for a unit change in an independent variable (assuming other variables remain constant), the core concept of SHAP involves using the Shapley values from cooperative game theory to quantify the impact of each individual feature on the model's predictions. SHAP decomposes the contribution of each prediction and allocates changes in the model's output to each feature, thereby providing a SHAP value for each feature. This approach not only helps in estimating the relative importance of features but also in analyzing how their interactions affect the model's predictive outcomes. The shapely values can be calculated via:

$$\emptyset_i = \sum_{S \subseteq N\{\, i\,\}} \frac{|S|!(n-|S|-1)}{n!} [v(S \cup \{\, i\,\} - v(S))] \tag{8}$$

Where $\emptyset_i$ represents the SHAP value of feature i; S is the subset of features; $N\{i\}$ data input; $|S|$ represents the number of features in S; n is the total number of features; $\frac{|S|!(n-|S|-1)}{n!}$ is the weighting of S; $[v(S \cup \{i\} - v(S))]$ is the feature's contribution of S.

SHAP transforms the Shapley value interpretation into an additive feature attribution method, allowing the interpretation of the model's predicted value as the cumulative sum of the attributed values for each input feature:

$$g(\mathcal{Z}') = \emptyset_0 + \sum_{i=1}^{M} \emptyset_i \mathcal{Z}_i' \tag{9}$$

Where $g(\mathcal{Z}')$ is the explanatory model; $\mathcal{Z}_i' \in \{0,1\}^M$ indicates whether the corresponding feature can be observed (1 or 0), M represents the number of input features. By incorporating SHAP values, it is possible to quantitatively assess the contribution of each feature to the model's predictions while also revealing complex nonlinear interactions between features. This approach significantly enhances the interpretability of traditional black-box models, providing more intuitive feature importance rankings and detailed analysis for nonlinear models. The additive nature of SHAP allows it to break down each feature's cumulative contribution to the final prediction, offering interpretability for complex machine learning models similar to that of linear models. Figure 7-2 illustrates the creation process of XGBoost and the interpretation of SHAP method.

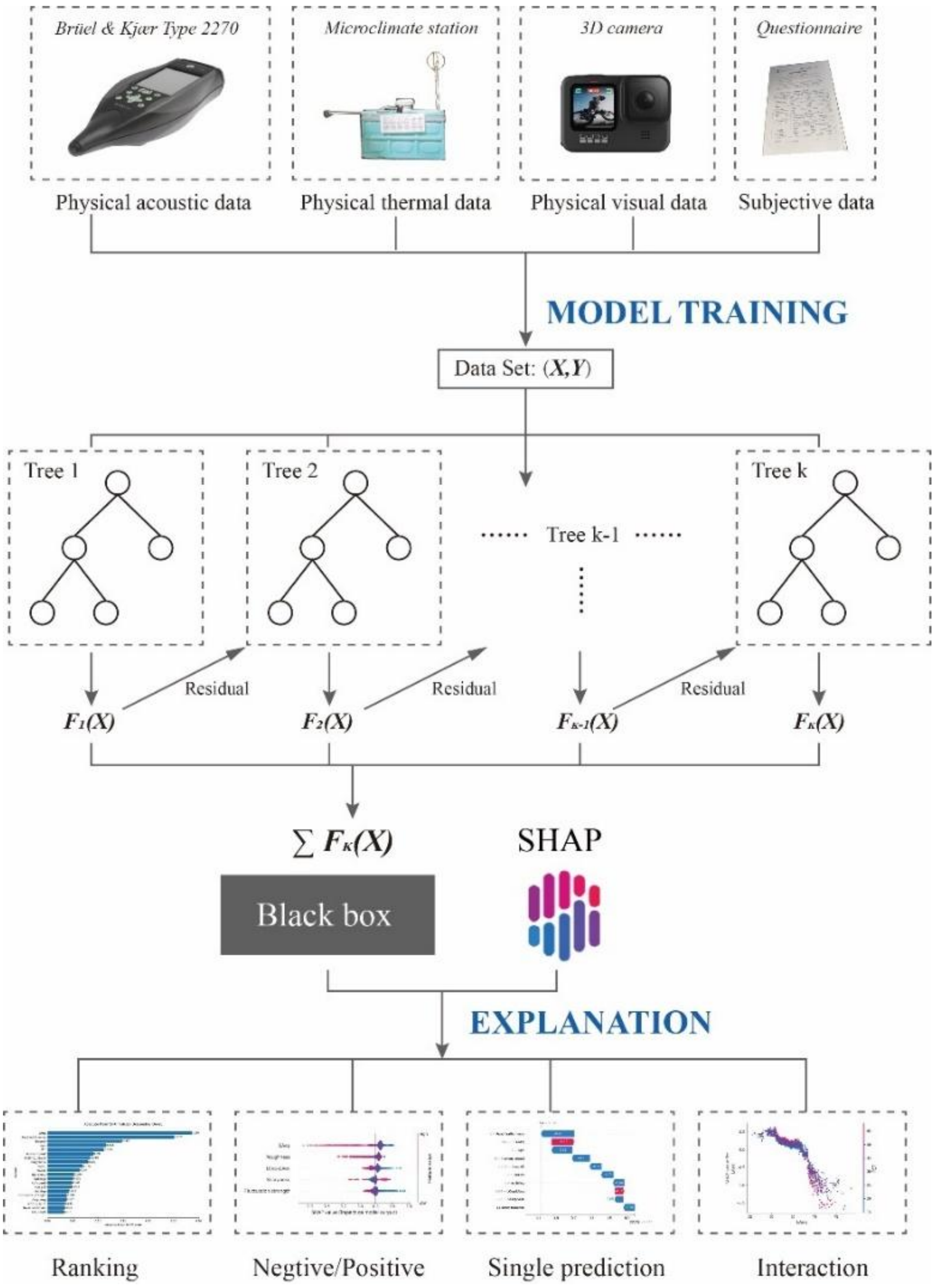


Figure 7-2 The model creation process of XGBoost and the interpretation of SHAP method

7.2.4 Performance of the prediction model

This study employed a standard stratified sampling method to split the data (around 1,800 valid responses) into a training set (80%) and a testing set (20%) for evaluating the performance of machine-learning models (Random Forest and XGBoost). Performance evaluation primarily relied on two metrics: correlation coefficient and RMSE. A correlation coefficient value closer to 1 and a RMSE value approaching 0 indicates better predictive model performance. For the linear regression model, the full dataset valid questionnaire responses and physical measurement data was directly used to develop the model, identifying ten significant features ($p < 0.05$). The model specification is presented in Equation (7), with a correlation coefficient of 0.497 and RMSE of 1.587. It should be noted that the model has only included those statistically significant features ($p < 0.05$), and all features had VIF values below 10, a widely accepted threshold for mitigating multicollinearity issues in developing MLR models.

$$Y = -0.209 * LAeq - 0.209 * RTN + 0.187 * Green\% - 0.127 * PET - 0.120 * Human + 0.106 * Leaves + 0.086 * Health + 0.056 * Bird - 0.071 * NS - 0.062 * Car + \varepsilon$$

(10)

Based on the same data set, XGBoost and Random Forest were developed by stepwise approach. In line with our hypothesis, both machine-learning models demonstrated superior predictive performance, highlighting their ability to capture complex relationships and interactions among features compared to multiple linear regression. A feature that was retained as inputs in machine-learning models met the following two criteria: it was a significant important feature, specifically that with a SHAP score > 0.025 (XGBoost)/ 0.021 (RF) (i.e., not less than one-tenth of the highest contribution).

XGBoost model was developed using a broader set of features, including physical features (physical acoustic, visual and thermal features), subjective perceptual data (RTN, Rail, Human, Bird, Leaves, Building), and personal characteristics (Age, NS, and Health). With this enriched feature set and more complex interactions, XGBoost outperformed RF, achieving a higher average correlation coefficient value of 0.707 and a lower RMSE value of 1.320.

The Random Forest model incorporated key objective features (physical acoustic, visual and thermal features) alongside subjective perceptual data (RTN, Rail, Human). The model has an average correlation coefficient value of 0.599 and an average RMSE value of 1.501. Table 7-3 presents the goodness-of-fit and hyperparameter values obtained for the optimal models using the Optuna framework. Given XGBoost's superior performance in predicting soundscape quality, the subsequent discussion focuses on its results to provide detailed insights into feature importance, non-linear relationships, and interactions.

Table 7-3 The goodness-of-fit and hyperparameter values of the optimal models

Soundscape quality		**XGBoost**	**Random forest**
Features		LA, S, R, Fls, LC-LA	LA, R, Fls, LC-LA
		Hue_S, People, Car, Green%, Sky%	Car, Green%, Sky%
		PET	PET
		RTN, Rail, Human, Bird, Leaves, Building	RTN, Rail, Human
		Age, NS, Health	
Train	Corr.	0.798	0.622
	RMSE	1.191	1.483
Test	Corr.	0.615	0.576
	RMSE	1.448	1.518
Mean RMSE		1.320	1.501
Mean Corr.		0.707	0.599
Hyperparameters		Max_depth: 5 Learning_rate: 0.015 N_estimators: 264 Subsample: 0.712 Colsample_bytree: 0.823 Reg_alpha: 0.032 Reg_lambda: 0.050 Gamma: 0.098 Min_child_weight: 9	Max_depth: 5 N_estimators: 251 Max_features: sqrt Min_samples_split: 2 Min_samples_leaf: 1 Bootstrap: True

7.2.5 Features importance ranking and positive or negative effects

Figure 7-3 shows the ranking order of feature importance determined based on the computed SHAP values. The horizontal axis represents the average of the sum of absolute

SHAP values across all samples, reflecting the magnitude of each input feature's contribution to the model's output. Figure 7-3 shows that LA_{eq} and perception of road traffic noise were the two most important features whose relative contributions > 0.25, which were remarkably higher than other features. They were followed by proportion of greenery (*Green%*), *PET* and age, each contributing 0.1-0.15 to soundscape quality evaluation. *Human_sound, roughness, rustling_leaves, health*, proportion of sky (*sky%*), hue standard deviation (*hue_std*), sharpness, and *rail_sound* were found to exert moderate influences on the soundscape quality evaluation (i.e., contributions between 0.05 and 0.1). The effect of the remaining features ranges from 0.03 to 0.05, indicating a relatively lower level of importance.

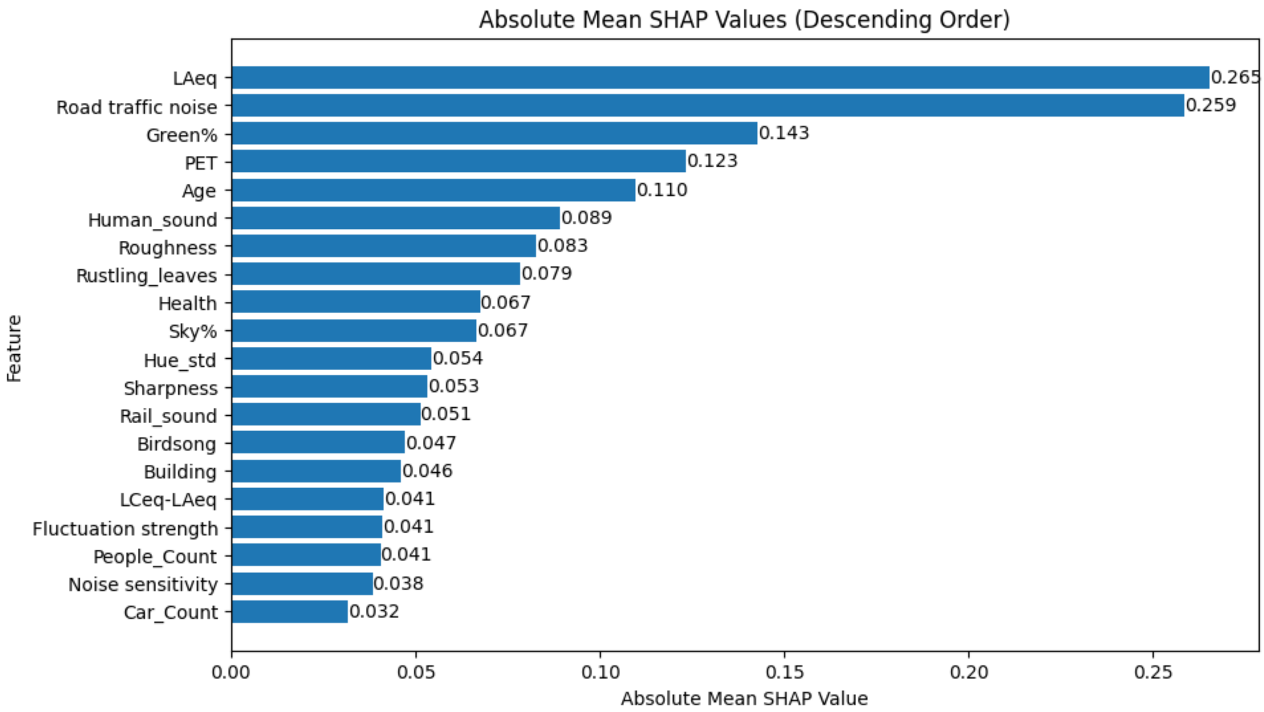


Figure 7-3 Summary plot showing the ranking order of features importance

In addition to ranking the order of importance, SHAP values can also help reveal the direction of influence (i.e., positive or negative) of features on the model's output (i.e., soundscape quality) through summary plots. Each point in Figure 7-4 denotes a SHAP value corresponding to a feature. On the y-axis, feature names are shown on the left with the feature values being indicated on the right (with colors transitioning blue-purple-red, signifying gradually increasing feature values), while their respective SHAP values are plotted on the x-axis.

Among all the objective physical and psycho acoustic parameters, LA_{eq} and fluctuation strength were found to exert negative influences on soundscape quality, suggesting higher LA_{eq} and fluctuation strength (Zwicker & Fastl, 1990) values produced lower soundscape quality (i.e., SHAP values) and vice versa. High levels of roughness (Zwicker & Fastl, 1990) tended to exert significant negative influences on soundscape quality. Among all the physical and psychoacoustic parameters, LC_{eq} - LA_{eq} exerted the weakest and negative influences on soundscape quality. The impact of sharpness (DIN 45692) on soundscape quality depends on the sound source. High sharpness values caused by birdsong exerted positive influences, while those caused by artificial sound sources (e.g., outdoor air conditioning units, power tooling and fire alarms) exerted negative influences. Other non-acoustic physical parameters including proportion of greenery, proportion of sky, and hue standard deviation were found to exert positive influences. Conversely, both number of people and cars exerted negative influences. Besides, thermal-related feature, *PET*, also exerted negative influences, and its size of influences became larger at higher feature values.

For subjective perceptual features, sounds from rustling leaves and birdsong exerted positive influences, while perception of dominance of road traffic sounds, human sounds, rail sounds, and perceptions of buildings exerted negative influences. Personal characteristics including *Age* and *Health* exerted positive influences, while *Noise Sensitivity* produced negative influences.

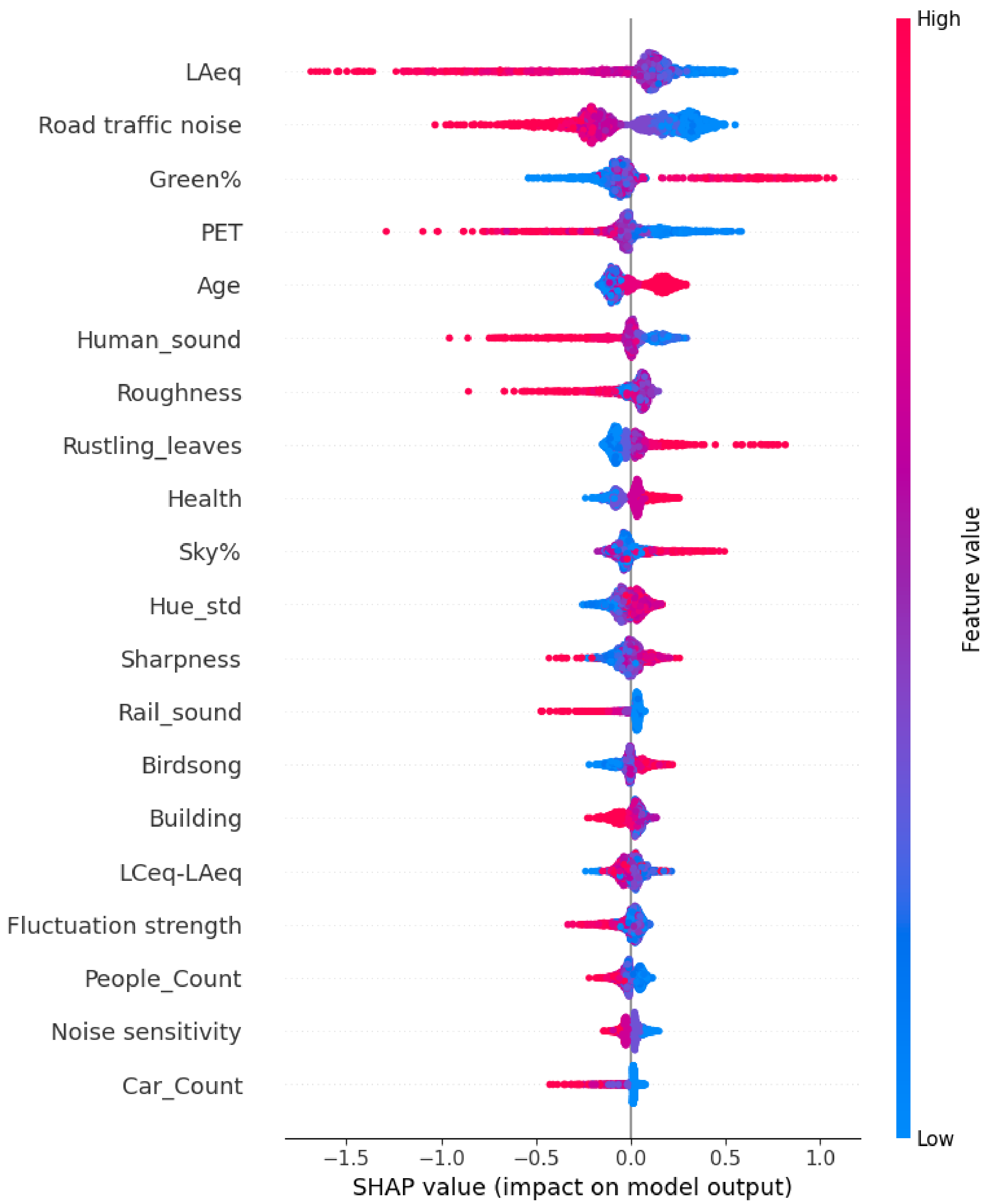


Figure 7-4 Summary plot showing the direction of influence of features

7.2.6 Single features analysis

Although the SHAP summary plots can help reveal the direction of feature influences, they are not able to reveal whether non-linear relationships exist between individual features and soundscape quality. To address this, a number of SHAP dependence plots have been developed for individual features. SHAP dependence plots are scatter diagrams whose x-axis depicts the feature value and y-axis depicts the SHAP value for that feature.

Within a limited context, this paper only reports on investigations circling around the three key features that determined to exert the most significant influences on soundscape quality: LA_{eq}, perception of road traffic noise, and proportion of greenery. As shown in Figure 7-5, LA_{eq} exerted negative influences on soundscape quality. The size of influence of LA_{eq} on soundscape quality gradually reduced when SHAP value decreased from 0.25 to 0 and LA_{eq} lied between 62 and 68 dBA. Conversely, the size of influence sharply increased with higher LA_{eq} values when LA_{eq} > 68 dBA. Likewise, road traffic noise exerted negative influences on soundscape quality and its size of influence varied with perceived dominance of road traffic noise. Its influence was positive when the perceived traffic noise was < 3 (a verbal scale of 0-10: 0 - 'Not at all', 5 - 'Moderately', and 10 - 'Completely dominated'), and its influence turned negative and surpassed 0.8 in certain instances when the rating of perceived dominance of road traffic noise > 7. In addition, greenery exerted positive influences on soundscape quality when *Green%* > 40%, no significant influences when 10% < *Green%* < 40%, and negative influences when *Green%* < 10 %.

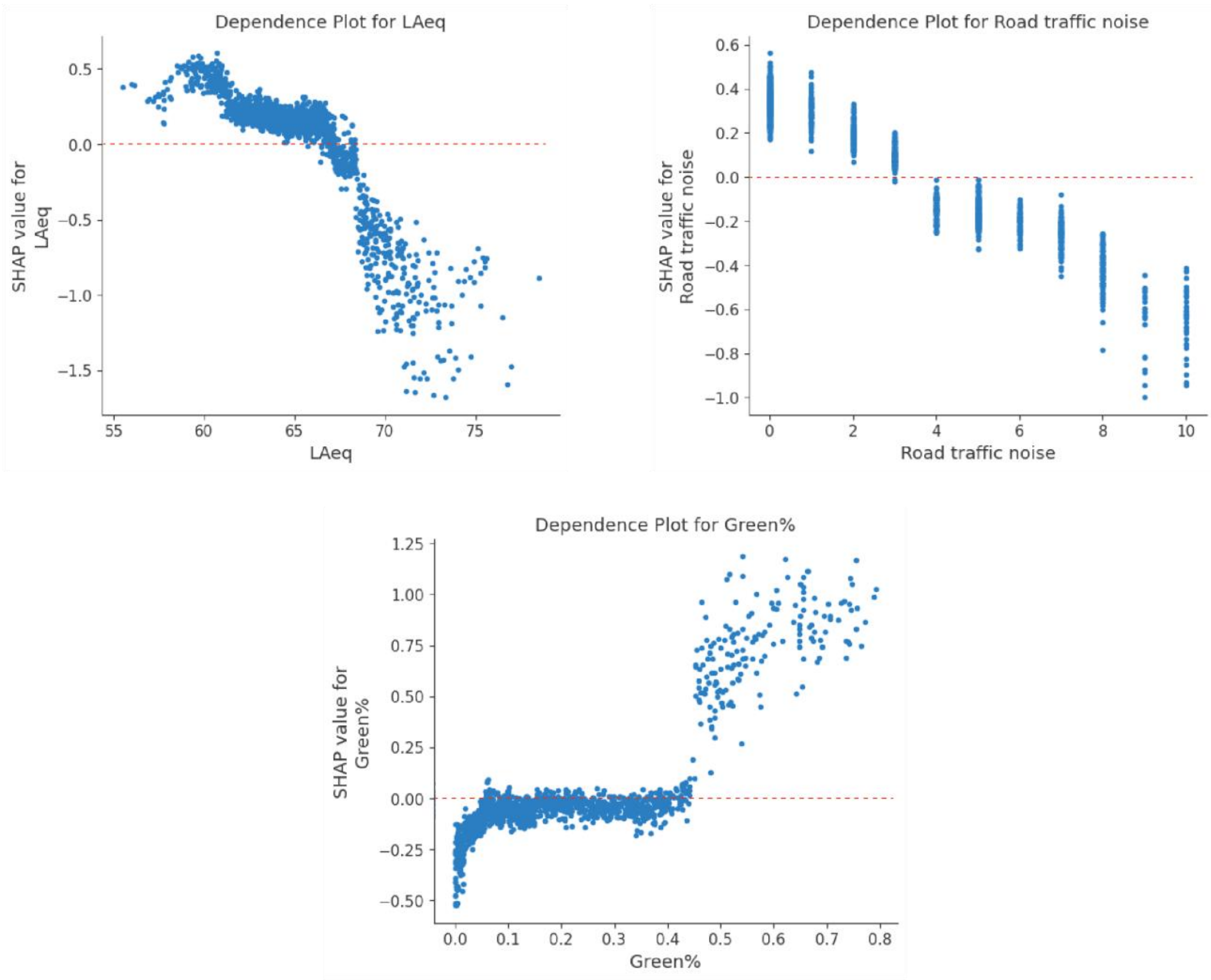


Figure 7-5 Dependency plots highlighting non-linear effects of individual features

7.2.7 Feature interaction effects

In addition to the nonlinear contributions of features to soundscape quality, dependency plots can also help to reveal the potential interactions as well as the nature of interactions between individual features. Specifically, the label of the interacting feature was introduced by the color gradient on the right vertical axis (from blue to red, i.e., feature value from low, medium to high) based on the basic SHAP summary plots. New plots can simultaneously display the impact of distribution changes of two features on SHAP values (See Figure 7-6).

Similar to what we reported previously, only three key interactions determined to exert the most significant influences on soundscape quality are going to be discussed here. Upon deeper examination, the size of interaction effects between "sound-heat" (LA_{eq} and *PET*), "sound-sound" (LA_{eq} and *RTN*), and "sound-vision" (LA_{eq} and *Green%*) obtained the highest mean absolute SHAP values of 0.045, 0.024, and 0.018, respectively (all others were below 0.015). This suggests that sound-heat interaction effect was larger in size than sound-sound interaction and in turn sound-vision interaction.

Notably, the size of interaction effects between LA_{eq} and *PET* also varied with their ranges of values. Higher *PET* values (i.e., > 35°C denoted by red point) was associated with lower SHAP values comparing to low and medium *PET* values (i.e., < 35°C denoted by blue and purple points) when the LA_{eq} > 68 dBA. Specifically, at LA_{eq} of 70 dBA, a *PET* of approximately 45°C corresponded to a SHAP value of about -1.2, whereas a *PET* value close to 30°C correlated with a SHAP value near -0.6. This suggested that high temperatures (i.e., *PET* > 35°C) significantly exacerbated the negative influences on soundscape quality when the LA_{eq} > 68 dBA. Likewise, high perceived road traffic noise (levels between 8 and 10) coupling with high levels of LA_{eq} (red points on the plot > 68 dBA) exacerbated the negative impact on the soundscape quality more than the combination of high perceived road traffic noise and mid/low levels of LA_{eq} (i.e., < 68 dBA denoted by blue and purple points). Also, the size of interaction effects between greenery and LA_{eq} were also found to vary with their ranges of values. A low greenery rate (i.e., < 10%) combining with a high LA_{eq} level (> 68 dBA denoted by red points) exacerbated its negative effects more than the combination of low greenery rate (< 10%) and low/medium LA_{eq} (< 68 dBA denoted by blue and purple points).

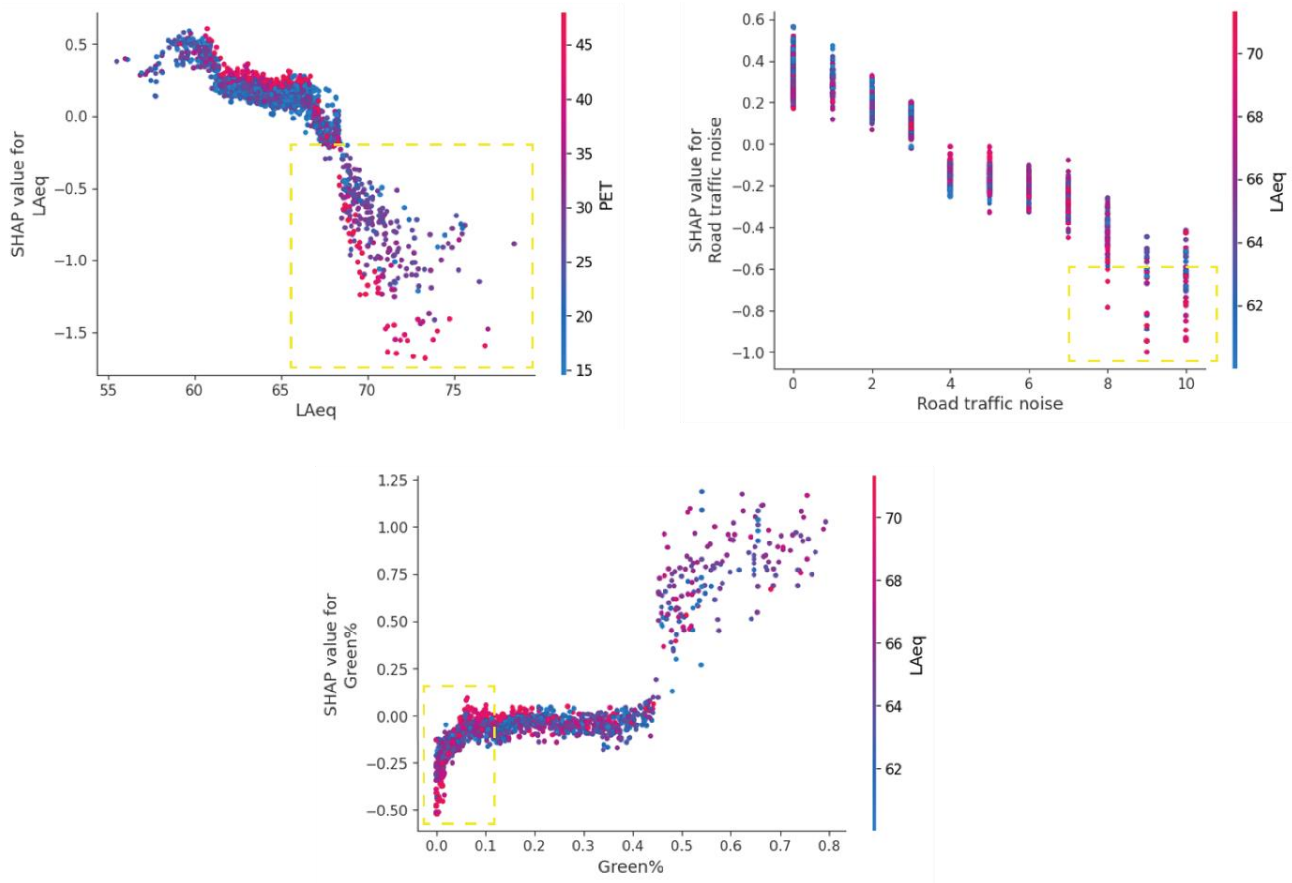


Figure 7-6 Dependency plots revealing interaction effects between features

7.3 Discussions

This study successfully developed an interpretable machine-learning model with the advanced learning algorithm XGBoost to predict the effects of aural, visual, and thermal environmental features on the soundscape quality in open spaces. Such holistic integration is rarely seen in earlier prediction models. Specifically, the model construction is based on both respondents' perceptual responses and the physically measured sound property and psychoacoustic data collected from previous large-scale field surveys conducted in public open spaces in Hong Kong. Through a comparison of the other models, the study reaffirmed previous findings that non-linear models significantly outperform traditional linear statistical models when applied to datasets with high contextual complexity and diverse sensory conditions

(Lionello et al., 2020). Recent studies have particularly suggested adopting ensemble learning algorithms (e.g., Random Forest (Wang et al., 2024; Wang et al., 2022)) to replace traditional machine-learning models (e.g., Support Vector Machines (Giannakopoulos et al., 2019) and Neural Networks (Yu and Kang, 2009)) due to their ability to enhance model accuracy and stability through the collaborative effects of multiple models. Building on this, the study further compared the more advanced XGBoost model with the popular ensemble learning algorithm, RF. The results demonstrated that XGBoost, leveraging its sophisticated gradient boosting framework, effectively captured complex feature interactions, non-linear relationships, and threshold effects, showcasing superior performance in predicting soundscape quality.

Moreover, to circumvent the drawbacks of "black box" nature of conventional machine-learning models, this study pioneers the application of SHAP method to unveil the ranking importance of features, the non-linear relationships between individual features and soundscape quality, and the nature of interaction effects between individual features. In addition, this study also highlights the significant impacts of thermal perceptions on the soundscape quality. Specifically, a number of observations arising from this study shed new lights on the soundscape design in public open spaces for enhancing social well-being.

First, the machine-learning model developed in this study has incorporated multiple facets of environmental features, confirming that soundscape evaluation indeed involves multisensory aural, visual, and thermal perceptions. Although the significance of audio-visual interaction has been repeatedly confirmed, the relative impacts of thermal perceptions on soundscape quality assessments have not been fully explored as thermal perceptions have not been integrated with other types of sensory perceptions into any prediction models. In our novel finding, *PET* emerged as the second most crucial non-acoustic factor influencing soundscape quality (SHAP value = 0.123). This indicates that thermal perceptions significantly impact soundscape assessments during hot seasons in a subtropical city, potentially leading to adverse effects on soundscape experience. Excluding thermal perceptions (e.g., PET) from the model results in a significant degradation in prediction performance, with the model's accuracy reducing by approximately 11% (i.e., the correlation coefficient value dropping from 0.707 to 0.614 and the RMSE value increasing from 1.320 to 1.471).

Second, LAeq was determined the most crucial factor (SHAP value = 0.265) influencing soundscape quality, and soundscape quality generally deteriorates with higher sound pressure level, which reaffirms with earlier soundscape findings (such as (Hong and Jeon, 2013; Lin et al., 2025)). In addition, our findings revealed that the influence of perceived road traffic noise (SHAP value = 0.259) was comparable to that of LAeq and their influences were significantly larger than other features. This is in line with the Wang et al.'s findings that LAeq was one of the two most important predictive features. In addition, this study found that the significance of perception of road traffic noise (SHAP value = 0.259) outweighed those of human voices (SHAP value = 0.089), rustling leaves (SHAP value = 0.079) or birdsong (SHAP value = 0.047). Notably, the perception of natural sound sources was determined to be less influential than the perception of road traffic noise and human voices. This finding diverges from the results reported by Ricciardi et al. and Wang et al. In particular, while bird songs are widely regarded essential components of a high-quality urban soundscape (Van Renterghem et al., 2020), their impact, indirectly represented by animal sounds in the questionnaire, was found to be lower than that of negative factors such as road traffic noise and human sound. This could be due to the lack of bird songs during many sampling periods in the surveys. Further research should be conducted to explore and better understand this difference. Furthermore, heightened sensitivity to road traffic noise may be attributed to the well-established Negativity Bias Theory (Rozin and Royzman, 2001) and Environmental Risk Perception Theory (Slovic, 1987), which suggest that individuals tend to prioritize environmental risks over benefits. Given the high-density urban context of Hong Kong, heavy traffic, high pedestrian density, and hot climate conditions exert a particularly strong negative influence on soundscape quality compared to other regions. Generally, the study's findings on subjective human perceptions of sound sources are in line with those revealed in previous research studies, suggesting that perceptions of non-natural sound sources (i.e., road traffic noise, human sound, and rail sounds) tended to lower soundscape quality ratings (Jeon et al., 2010; Lugten et al., 2018), whereas perceptions of natural sounds including rustling leaves and birdsong enhanced it (Hong et al., 2020b; Jeon et al., 2010; Lugten et al., 2018).

Psychoacoustic parameters including roughness and fluctuation strength were found to exert moderate and negative influences on the model's prediction (i.e., contributions between 0.05 and 0.1). This aligns with negative roughness's influences as revealed by (Derya ÇAKIR AYDIN, 2016; Tan et al., 2022) but was in divergence with negative sharpness's influences revealed by (Derya ÇAKIR AYDIN, 2016; Hong and Jeon, 2017a). In this study, high sharpness values (illustrated in the form of red points) exhibit both positive and negative SHAP values, indicating that its effect on soundscape quality is not uniform. This observation supports the hypothesis that the influence of psychoacoustic parameters is source-dependent. Previous studies have shown that sharpness from water sounds can enhance soundscape perception, whereas sharpness from traffic noise tends to degrade it (Maristany et al., 2016). The bidirectional distribution of sharpness's influence suggests that the model captures such source-specific variations. In comparison, linear models may oversimplify the complex relationships between psychoacoustic parameters and soundscape quality. Non-linear methods offer a more flexible framework to capture threshold effects and source-specific variations inherent in these relationships. For instance, the influence of a sound source on soundscape perception is often jointly modulated by its type and intensity — an interaction commonly observed in real-world environments but difficult to predefine using linear assumptions. Moreover, non-linear models are capable of automatically identifying context-sensitive interactions without the need for manually specifying interaction terms. Identifying such dynamic interactions — i.e., interactions that emerge only under specific combinations of environmental features — is particularly critical in the context of urban open spaces, where environmental conditions are highly variable and the relationships among features tend to be more complex. Adopting non-linear approaches allows for the identification of subtle turning points and dynamic interactions between factors, defined as the continuous and reciprocal exchange or relationship between factors that change an evolve over time. These interactions are not static; they adapt and adjust based on the actions or states of the involved factors (Faiciuc, 2023). Consequently, non-linear approaches offer a more accurate understanding of their contributions to soundscape quality.

In addition, the importance of noise sensitivity was found to be relatively low yet significant in this study. While other studies have investigated its role in soundscape evaluation, its size of influence appears to be highly context-dependent rather than universally significant. Some studies suggest that noise sensitivity significantly affects soundscape evaluation in environments with high noise exposure levels, such as residential areas heavily impacted by traffic noise (Shepherd et al., 2015; Van Renterghem and Botteldooren, 2012). Conversely, other research indicates that noise sensitivity is a weaker predictor in high-quality sound environments, as it fails to effectively capture individual differences in the perception of positive environmental stimuli (Gao et al., 2023). Moreover, even in high-noise environments, it is not necessarily the dominant factor influencing soundscape perception. Research suggests that sound pressure level and perceptions of sound sources often play a more critical role in shaping overall soundscape quality. Given that this study encompasses a wide range of urban open spaces with varying soundscape qualities, the lower predictive power of noise sensitivity is not unexpected. This suggests that in open and dynamic outdoor urban environments, soundscape perception may be more strongly influenced by environmental attributes (e.g., sound source composition, visual context) rather than personal noise sensitivity traits.

Third, our findings also revealed greenery as the most significant non-acoustic factor affecting soundscape quality (SHAP value = 0.143), second only to LA_{eq} and perception of road traffic noise. This finding aligned with Zhao et al.'s study, which utilized 28 visual features for semantic segmentation to predict soundscapes, revealing the percentage of vegetation pixels as the most important positive feature for predicting sound quality. Given the significant contribution of greenery to soundscape quality, numerous studies have explored its impact under different sound environments. For instance, Pheasant et al. revealed that 10% natural features could achieve an effect equivalent to reducing noise levels by 3 dBA when studying tranquility for countryside. Similarly, Leung et al. reported that the positive effects of greenery even outweigh those of water features in urban areas. In addition, a threshold effect of greenery coverage has been determined for soundscape evaluation. For example, Ren et al. found that 15-35% greenery coverage could significantly enhance soundscape evaluations more than 0-15% at moderate road traffic noise levels (50-60 dBA). However, at higher noise levels (65-70 dBA), only 20-35% greenery coverage was effective in improving soundscape quality. Regarding the impact of road traffic noise, Van Renterghem (Van Renterghem, 2019) summarized a general pattern: at higher sound pressure levels, the influence of green views on soundscape perception becomes more pronounced compared to lower road traffic noise levels. However, under extreme conditions (e.g., 40 dB or 90 dB), the visual component no longer significantly affects loudness perception. Furthermore, Van Renterghem et al. (Van Renterghem et al., 2023) specifically emphasized the importance of green quality, noting that when the amount of greenery approaches an optimal level, colorful and species-rich vegetation can further enhance its positive effects.

While LA_{eq}, perception of road traffic noise (Ricciardi et al., 2015; Wang et al., 2022), and greenery percentage (Leung et al., 2017; Pheasant et al., 2010) have consistently been emerged as key features influencing soundscape quality, there remains a gap in our understanding of the precise relationships between these features and soundscape quality. The results from SHAP-based dependency plots have confirmed the earlier findings reported by (Fan et al., 2016; Yu and Kang, 2009) in their systematic reviews that their relationships were in fact non-linear. Conceivably, more accurate results can be gained by using non-linear method to understand the relationship between soundscape evaluation and influential features (Lionello et al., 2020). First, LA_{eq} exerted negative influences on soundscape quality and the size of contribution sharply increased with higher LA_{eq} values when LA_{eq} exceeds 68 dBA. Likewise, the perceived dominance of road traffic noise was negatively correlated with soundscape quality and its negative effect was significantly intensified when its rating was higher than 7. In addition, greenery had positive influences on soundscape quality when *Green%* > 40% and exerted a negative impact when *Green%* < 10 %, but its impact on the soundscape quality was not significant when the green% was between 10% and 40%.

Fourth, the SHAP dependency plots suggested significant interaction effects between LA_{eq} and specific visual and thermal features as well as other sound related features. Notably these interactions include "sound-vision" (LA_{eq} and *Green%*), "sound-heat" (LA_{eq} and *PET*), and "sound-sound" (LA_{eq} and *RTN*). Interestingly, their sizes of interaction effects sometimes outweigh those of some of the main effects of individual features, emphasizing their importance in soundscape assessments. Insights from the sound-heat interaction revealed that extreme high temperatures (> 35°C) and high sound pressure levels (> 68 dBA) significantly intensified the adverse influences on soundscape quality. This finding aligns with controlled laboratory experiments (Wen et al., 2025), which observed that acoustic comfort voting (ACV) scores were highest at lower temperatures (18–20°C) when sound pressure levels were high

(65–80 dBA). These results suggest that thermal perception modulates acoustic comfort differently under varying SPLs, with lower temperatures mitigating the negative impact of high noise levels in controlled settings. Similarly, the "sound-sound" interaction effect existed with high perceived road traffic noise levels (levels 8 to 10) and high sound pressure level (> 68 dBA) aggravated the negative influences on soundscape quality. This implicitly suggested that urban designs should strive to avoid the concurrent existence of high sound pressure environments, high temperatures, and high subjective road traffic noise perceptions, as this will produce synergistic effects that severely compromise soundscape quality. Upon detailed analysis of effect of proportion of greenery, it was revealed that soundscape quality would not be significantly improved by increasing the proportion of greenery if the final proportion of greenery in the view did not exceed 40%. Furthermore, the nature of interaction effect found between proportion of greenery and LA_{eq} suggested that a greenery proportion of below 10% together with high LA_{eq} levels (> 68 dBA) exacerbated its negative effects more than those at low/medium (< 68 dBA) LA_{eq} levels.

Given the above findings, this study suggests that incorporating multisensory environmental design and a layered strategy based on the nature of nonlinear feature interactions (e.g., threshold effects) can effectively enhance soundscape quality. Firstly, multisensory design emphasizes the integration of visual, auditory, and thermal perception elements to improve the soundscape. For example, adding water features (Huang et al., 2024; Lai et al., 2019), increasing greenery (Chan et al., 2017; Huang et al., 2024; Lai et al., 2019), and introducing shade structures (Chan et al., 2017) can mitigate the negative effects of high temperatures on soundscapes, providing a more comfortable visual and thermal experience. Additionally, noise control measures, such as traffic management (Jiang et al., 2018), sound barriers (Hong and Jeon, 2014), and green or water buffer zones (Hong et al., 2020a), help reduce noise levels (LA_{eq}) and low-frequency noise transmission, alleviating road noise interference in soundscapes. Similarly, introducing masking sounds like water and bird sounds (Van Renterghem et al., 2020), especially when the water sound pressure level is close to that of traffic noise (Li et al., 2024), can further improve soundscape quality. Based on SHAP analysis results, soundscape design can also benefit from a layered approach to nonlinear feature interactions, particularly in optimizing “sound-heat” and “sound-sound” interactions. For instance, to reduce the combined impact of high temperature and high noise levels, cooling facilities can be installed in transport hubs, or shaded quiet zones can be designated in open, sun-exposed areas, thereby alleviating the compounded effects of thermal perception and noise. Likewise, to optimize “sound-sound” interactions, traffic barriers or soundproofing facilities can be set up in high sound pressure areas to mitigate the combined impact of high sound pressure levels and high perceived traffic noise on soundscape quality.

7.4 Conclusion

All in all, this study using the developed machine-learning model, explored the determinants of soundscape quality in open spaces from a multisensory perspective, revealing the complex influence of auditory features, visual environment, and microclimate conditions on soundscape experience. The study particularly highlights the critical role of thermal perception in soundscape quality, with a pronounced impact on soundscape evaluation in high-temperature settings. Additionally, SHAP analysis provided insights into the ranking of feature importance, the non-linear relationships between features and soundscape quality, and interactions among features. Results indicate that interactions between *LAeq* and specific visual, thermal perception, and other sound-related factors significantly affect soundscape quality assessments. These findings hold important practical value, offering an effective reference framework for optimizing key factors that influence soundscape quality.

Despite its significant contributions, this study bears a number of limitations on the applicability of the formulated model. First, as the data were primarily collected in Hong Kong, the findings might be most relevant to high-density urban city areas with abundant auditory and landscape resources. Second, the conclusions might not be applicable to colder regions or winter conditions as our data were mainly collected during hot climate. Third, the study focused on the impact of environmental features on soundscape quality, but did not consider the influences of human activity pattern and their interactions. Fourth, this study was intended to provide government officials a simplified metric for describing overall soundscape quality from an administrative perspective. While soundscape quality provides a holistic and comparable metric, it may not fully capture the nuanced perceptual differences across various urban environments. The affective dimensions of pleasantness and eventfulness can offer a more refined understanding of how different functional areas contribute to soundscape perception. Future research efforts will be directed towards integrating multidimensional descriptors into predictive models to enhance the adaptability of soundscape assessments across diverse urban settings, as we have also included perceived affective quality in our questionnaire form. Fifth, the determination of interaction thresholds in this study was data-driven, relying on pattern recognition within SHAP dependence plots. While this approach allows for an empirical understanding of non-linear effects, the exact breakpoints are not strictly mathematical thresholds but rather representative values observed in the transition regions. Future research should consider alternative statistical techniques, such as quantile regression or non-parametric change point detection, or controlled experiments to further verify these thresholds under various urban environmental conditions. Sixth, this study employed simplified self-reported measures for noise sensitivity rather than fully validated standardized scales. While the five-point Likert scale used for noise sensitivity assessment aligns with approaches adopted in some environmental psychology and noise perception research, more comprehensive instruments, such as the Weinstein Noise Sensitivity Scale (WNSS), could provide a more detailed evaluation of individual differences. The decision to use simplified scales was made to balance survey efficiency and respondents' burden, particularly in a large-scale field study. However, future research should consider incorporating validated instruments to enhance the robustness and comparability of these self-reported measures. Seventh, this study primarily considered green quantity, measured as the percentage of vegetation coverage, but did not explicitly account for green quality, such as vegetation diversity, species richness, or color variations. While previous studies have highlighted that green quality can further enhance the positive effects of greenery on soundscape perception, particularly when green quantity reaches an optimal level, its role remains unexamined in this study. Future research should integrate both quantity and quality measures of greenery to provide a more comprehensive understanding of their combined effects on urban soundscapes. Finally, some evaluations of sound sources and visual elements in the study were based on subjective perceptions, which could be influenced by personal preferences, psychological states, and cultural backgrounds. Addressing these limitations in future research studies will help to acquire more comprehensive and precise understandings.

Chapter 8 Conclusions and recommendations for future work

8.1 Conclusion

This thesis systematically investigated the impacts of multisensory and multifunctional factors on the soundscape quality of urban open spaces. By employing a multi-dimensional analytical approach and modeling techniques, it develops a comprehensive framework that captures the intricate relationships between auditory, visual, and thermal inputs, as well as the role of micro-scale functional spaces and associated activities. This integrated framework provides a deeper understanding of the mechanisms shaping soundscape evaluations, offering a foundation for more accurate assessments and evidence-based strategies for optimizing urban open spaces.

First, this study redefined the evaluation perspective of soundscape quality by incorporating sensory inputs, environmental contexts, and activity characteristics. Unlike traditional noise-based assessments that focus primarily on physical acoustic properties, this research emphasized the perceptual and cognitive dimensions of soundscapes as shaped by multisensory integration. The findings from correlation analyses and qualitative sound mapping confirmed that nature-related elements, such as birdsong and greenery, significantly enhance soundscape evaluations, while anthropogenic factors, such as road traffic noise and dense building structures, negatively impact perceived soundscape quality. Furthermore, activity types and spatial configurations within functional spaces played a crucial role, particularly in multifunctional urban spaces where variations in activity timing, density, and distribution influenced multidimensional sensory experiences. These findings underscore the importance of integrating environmental and social dynamics into soundscape assessments, moving beyond static, one-dimensional models.

Second, to further refine the theoretical framework, Chapter 5 developed a structural equation model (SEM), systematically analyzing both direct and indirect determinants of soundscape quality. The results highlighted the dominant influence of pleasantness (relative influence = 0.327), surpassing physical acoustic properties, as a key factor driving soundscape quality. Visual quality exhibited comparable importance (relative influence = 0.302), emphasizing its regulatory role in soundscape perception. Thermal factors, such as thermal acceptability, while having a smaller impact (relative influence = 0.129), also played a critical role through their interactions with auditory and visual perceptions. The model further demonstrated that perceived dominance of specific sound sources significantly influenced pleasantness and, consequently, soundscape quality. For instance, the perceived dominance of birdsong ($\beta = 0.065$) improved pleasantness, whereas road traffic noise ($\beta = -0.254$) and human sounds ($\beta = -0.147$) reduced it. These findings suggest that reducing exposure to disruptive sounds, such as road traffic, and enhancing exposure to natural sound sources, such as birdsong or water features, could serve as effective noise-masking and mitigation strategies. Moreover, visual elements such as greenery coverage were shown to improve soundscape quality by reducing noise sensitivity and enhancing positive emotional responses.

While the SEM model effectively captured the impact of multisensory factors, it was somewhat limited in its ability to account for the role of activity-based determinants. To address this gap, an ordinal logistic regression model was employed to further investigate the influence of microscale functional spaces and ongoing activities on soundscape evaluation. The results confirmed that microscale spatial contexts significantly shape soundscape perception, although their effects were weaker than those of place-based factors (relative influence ratio of approximately 1:3). For example, children's play activities in designated playgrounds were found to enhance vibrancy and liveliness, whereas mechanical noise in sitting-out areas reduced perceived tranquility. Additionally, the rustling of leaves was shown to improve perceived calmness in resting areas. The findings reinforce the notion that soundscape quality is not solely dictated by sensory characteristics but is also influenced by functional zoning and the nature of activities occurring within the space. These insights highlight the need for urban planners to account for dynamic spatial functions when designing public open spaces that promote positive soundscape experiences.

Despite the effectiveness of statistical models in identifying key determinants, traditional linear approaches were insufficient in capturing the inherently nonlinear relationships among multisensory inputs. To overcome this limitation, this research introduced a machine learning framework, employing the XGBoost algorithm, to develop a predictive model that more accurately reflects the complexity of soundscape evaluation. Model interpretation using SHAP (Shapley Additive Explanations) analysis identified LAeq (SHAP value = 0.265), perceived road traffic noise (SHAP value = 0.259), greenery coverage (SHAP value = 0.143), and PET (SHAP value = 0.123) as the primary determinants of soundscape quality. Furthermore, the analysis revealed significant interaction effects, such as "sound-visual" (e.g., LAeq and greenery coverage) and "sound-thermal" (e.g., LAeq and PET), emphasizing the importance of accounting for cross-modal effects in soundscape assessments.

Notably, the study found that soundscape quality deteriorated significantly when sound pressure levels exceeded 68 dBA, particularly in conjunction with high temperatures exceeding 35°C. Similarly, greenery coverage above 40% had a pronounced positive effect, whereas coverage below 10% resulted in negative impacts. These findings suggest that urban soundscape optimization should not only focus on controlling noise levels but also consider broader environmental modifications, such as increasing vegetation cover and improving thermal comfort conditions. By leveraging machine learning techniques, this research provided a more robust, data-driven approach to predicting soundscape quality, offering new possibilities for real-time soundscape monitoring and adaptive urban design strategies.

In conclusion, this research makes several key contributions to the field of soundscape evaluation. First, it advances the theoretical understanding of soundscape perception by integrating multisensory and multifunctional factors within a structured evaluation framework. Second, it empirically validates these relationships using advanced statistical and machine learning models, demonstrating the importance of cross-modal sensory interactions. Third, it provides practical insights for urban planners and policymakers, emphasizing the need for holistic urban design strategies that enhance both auditory and non-auditory environmental qualities.

8.2 Recommendations for future work

Future research should extend the scope of investigation to encompass a broader range of urban environments and climatic conditions. This study primarily focused on high-density, subtropical cities where multisensory and multifunctional factors were analyzed within the context of public open spaces. However, the interactions among auditory, visual, and thermal inputs, as well as the impact of micro-scale functional spaces and ongoing activities, may exhibit significant variations in different urban morphologies and climatic zones. Cities in cold regions may present distinct soundscape characteristics due to differences in seasonal weather patterns, environmental sound sources, and urban design principles. For instance, in cold climates, where snow and ice modify the acoustic environment and pedestrian activities shift seasonally, the relative importance of different sensory inputs may vary. In arid regions, where high temperatures and sparse vegetation are dominant features, thermal perception may exert a stronger influence on soundscape evaluations than in other climatic contexts. Conducting comparative studies across multiple cities with varying urban densities, spatial configurations, and socio-cultural contexts would enhance the generalizability of the proposed framework. These comparative analyses would enable researchers to identify context-specific differences and develop more adaptable guidelines for soundscape optimization in diverse urban environments.

While this study employed kinds of data collection methods such as questionnaire surveys, on-site measurements, soundwalks and sound maps, soundscapes are inherently dynamic, shaped by temporal fluctuations in human activities, traffic patterns, weather conditions, and social interactions. As urban environments evolve throughout the day and across seasons, soundscape perceptions also shift in response to these changes. Future research should integrate dynamic and real-time methodologies to better capture these temporal variations. Advanced sensor technologies, mobile applications, and Internet of Things (IoT)-enabled monitoring systems offer promising tools for tracking real-time changes in soundscape quality. By deploying distributed sensor networks in public open spaces, researchers could continuously collect data on sound pressure levels, thermal conditions, and visual stimuli while simultaneously analyzing user responses in real-time. Mobile applications equipped with participatory sensing capabilities could allow residents to contribute perceptual evaluations at different times of the day, enabling a more granular understanding of how soundscapes fluctuate across temporal scales. Additionally, real-time monitoring systems could be used to develop adaptive management strategies for urban soundscapes, allowing planners and policymakers to respond dynamically to emerging environmental and social conditions. Such systems would provide an invaluable evidence base for designing open spaces that are resilient to changing urban dynamics and climatic variability.

While this study demonstrated that activity-based factors play a critical role in shaping soundscape quality, these findings were based on cross-sectional data, which provide only a snapshot of soundscape perceptions at specific points in time. However, human-environment interactions are highly dynamic, and individuals may exhibit adaptive behaviors in response to long-term exposure to different sound environments. Future studies should conduct longitudinal research to investigate how soundscape evaluations evolve over extended periods and how users adapt to varying acoustic and environmental conditions. For instance, examining how seasonal variations in human activity patterns influence soundscape quality could provide deeper insights into the temporal dynamics of sound perception. Furthermore, longitudinal studies could track how repeated exposure to certain sound environments influences cognitive and emotional responses, contributing to a more comprehensive understanding of the long-term impacts of soundscape design.

While this thesis focused on soundscape quality as a holistic indicator, this approach may ignore differences among distinct perceptual dimensions that collectively shape the soundscape experience. Specifically, indicators of perceived affact quality such as pleasantness and eventfulness—two key affective dimensions widely recognized in soundscape research—capture different aspects of auditory perception and emotional responses. Pleasantness generally reflects the overall favorability or comfort of the sound environment, while eventfulness relates to its liveliness, complexity, or degree of stimulation. These dimensions often interact but can exhibit divergent patterns under different environmental and functional contexts. Future studies should therefore adopt an approach that separately models these affective components to provide a more granular understanding of how different factors influence the specific emotional and psychological dimensions of soundscape perception. By incorporating multiple perceptual indicators, researchers can uncover more complex and context-sensitive relationships among sensory inputs, spatial functions, and user activities.

Additionally, virtual reality (VR) simulations and immersive soundscape experiments could be employed to model potential future scenarios and test different urban design interventions. By simulating various spatial configurations, sound source distributions, and environmental conditions, researchers could assess how changes in urban form and functional zoning influence soundscape perceptions before actual implementation. Such experimental approaches would offer a cost-effective and efficient means of optimizing urban soundscapes, allowing planners to refine design strategies based on empirical evidence.

Future research should aim to expand the geographic and climatic scope of soundscape studies, integrate real-time monitoring techniques, enhance the interpretability of predictive models, and conduct longitudinal assessments of activity-based influences. By advancing these research directions, scholars can refine theoretical frameworks, improve methodological approaches, and develop evidence-based recommendations for enhancing soundscape quality in urban open spaces. Ultimately, these advancements will contribute to creating more inclusive, adaptable, and sustainable urban environments that prioritize multisensory well-being.

APPENDIX

有關城市聲景的問卷調查

Questionnaire on urban soundscape

您好，我是香港理工大學建築環境及能源工程學系的學生，現在進行一項有關城市聲景的問卷調查，以此了解城市景觀對噪音滋擾和環境感知的影響。完成問卷約 5 到 10 分鐘。

本次問卷調查為自願參與形式，您所提供的資料只會用作日後研究及發表，但是您的隱私權將得以保留，即您的個人資料不會被公開。

Hello, I am a student in the Department of Building Environment and Energy Engineering at the Hong Kong Polytechnic University. I am conducting a survey on urban soundscape. It takes about 5 to 10 minutes to complete the questionnaire. This survey is voluntary. The information you provide will only be used for future research and publication. However, your privacy will be preserved, i.e. your profile will not be made public.

第1部 – 聲源識別 **Sound source identification**	1. 您認為目前所聽到以下5種聲音分別達到甚麼顯著差異程度？ **To what extent do you presently hear the following 5 types of sounds?**
A. 道路交通 (汽車、貨車、巴士聲等) **Road traffic noise** (e.g. cars, trucks, buses etc.)	Not at all 完全聽不到 — Moderately 中等顯著 — Dominates completely 最顯著 0 1 2 3 4 5 6 7 8 9 10
B. 鐵路交通 (港鐵、火車聲等) **Rail traffic noise** (e.g. MTR)	Not at all 完全聽不到 — Moderately 中等顯著 — Dominates completely 最顯著 0 1 2 3 4 5 6 7 8 9 10
C. 人聲 (對話) **Human sounds** (e.g. conversation)	Not at all 完全聽不到 — Moderately 中等顯著 — Dominates completely 最顯著 0 1 2 3 4 5 6 7 8 9 10
D. 動物 (鳥鳴、蟬聲等) **Animal sounds** (e.g. birds, cicadas)	Not at all 完全聽不到 — Moderately 中等顯著 — Dominates completely 最顯著 0 1 2 3 4 5 6 7 8 9 10
E. 天然環境 (樹葉聲) **Sounds due to the elements** (e.g. leaves)	Not at all 完全聽不到 — Moderately 中等顯著 — Dominates completely 最顯著 0 1 2 3 4 5 6 7 8 9 10
第2部 – 大自然聲音 **Natural sound preference**	2. 您如何評價您對所聽到的大自然聲音？ **Please give your rating on the preference for the natural sound you just heard?** 非常不喜歡 **Very much dislike** — 一般 **Neutral** — 非常喜歡 **Very much like** 1 2 3 4 5
A. 雀鳥聲音 **Birdsong**	3. 您對以下兩種聲音感到**緊張或放鬆**？ **For each of the 2 sounds below, do you feel stressful or relaxing?** Very stressful 非常緊張 — Neutral 不受影響 — Very relaxing 非常放鬆 1 2 3 4 5
B. 樹葉聲音 **Rattling leaves**	Very stressful 非常緊張 — Neutral 不受影響 — Very relaxing 非常放鬆 1 2 3 4 5
第3部 – 感知的情感質量 **Perceived affective quality**	4. 就以下8種對目前四周聲音環境的感受，您贊同或不贊同的程度是... **For each of the eight scales below, to what extent do you agree or disagree that the present surrounding sound environment is...**
A. 悅耳 **Pleasant**	Strongly disagree 非常不同意 — Neutral 中立 — Strongly agree 非常同意 0 1 2 3 4 5 6 7 8 9 10

B. 混亂 Chaotic	0 1 2 3 4 5 6 7 8 9 10
C. 充滿生氣 Vibrant	0 1 2 3 4 5 6 7 8 9 10
D. 平淡 Uneventful	0 1 2 3 4 5 6 7 8 9 10
E. 平靜 Calm	0 1 2 3 4 5 6 7 8 9 10
F. 滋擾 Annoying	0 1 2 3 4 5 6 7 8 9 10
G. 豐富 Eventful	0 1 2 3 4 5 6 7 8 9 10
H. 單調 Monotonous	0 1 2 3 4 5 6 7 8 9 10

第4部 – 整體聲音環境與戶外空間環境
Overall sound environment and open space environment

5. 整體上您如何評價這個屋邨的聲音環境？

How would you describe the overall sound environment of the estate?

Very bad 非常差 — Neutral 一般 — Very good 非常好

0 1 2 3 4 5 6 7 8 9 10

6. 整體上您如何評價這個屋邨的戶外空間環境？

How would you describe the overall open space environment of the estate?

Very bad 非常差 — Neutral 一般 — Very good 非常好

0 1 2 3 4 5 6 7 8 9 10

7. 整體上您認為四周聲音環境對符合目前所在空間達到怎樣程度？

Overall, to what extent is the present surrounding sound environment appropriate to the present open space?

Not at all 完全不符合 — Moderately 中等符合 — Perfectly 完全符合

0 1 2 3 4 5 6 7 8 9 10

第5部 – 目前戶外空間環境與景觀特徵
Present landscape, open space environment and landscape characteristics

8. 您如何評價目前的景觀？

How would you describe the present landscape?

Very bad 非常差 — Neutral 一般 — Very good 非常好

0 1 2 3 4 5 6 7 8 9 10

9. 您如何評價目前的戶外空間環境？

How would you describe the present open space environment?

Very bad 非常差 — Neutral 一般 — Very good 非常好

0 1 2 3 4 5 6 7 8 9 10

10. 您就現在身處環境看到以下4種景觀特徵達到甚麼顯著差異程度？

To what extent do you presently see the following 4 types of landscape characteristics?

A. 車路 Road	Not at all 完全看不見 — Moderately 中等顯著 — Extremely prominent 極顯著 0 1 2 3 4 5 6 7 8 9 10
B. 建築物 Building	Not at all 完全看不見 — Moderately 中等顯著 — Extremely prominent 極顯著 0 1 2 3 4 5 6 7 8 9 10
C. 綠化 Greenery	Not at all 完全看不見 — Moderately 中等顯著 — Extremely prominent 極顯著 0 1 2 3 4 5 6 7 8 9 10

D. 天空 Sky	Not at all 完全看不見 0 – 1 – 2 – 3 – 4 – 5 Moderately 中等顯著 – 6 – 7 – 8 – 9 – 10 Extremely prominent 極顯著
第6部 – 就目前環境對熱感到舒適的程度 Thermal sensation and thermal comfort of the present environment	11. 您現在感覺到… How do you feel right now? Cold 冷 -3 – Cool 涼 -2 – Slightly cool 有點涼 -1 – Neutral 中性 0 – Slightly warm 有點暖 1 – Warm 暖 2 – Hot 熱 3
	12. 您就現在身處環境對熱感到舒適的程度如何？ How would you rate the thermal comfort of the present environment? Extremely uncomfortable 極不舒適 0 – 1 – 2 – 3 – 4 – 5 Comfortable 舒適 – 6 – 7 – 8 – 9 – 10 Extremely comfortable 極舒適
	13. 您就現在身處環境您對熱感到舒適的接受程度如何？ Do you find the thermal comfort of the present environment acceptable? Extremely unacceptable 極不接受 0 – 1 – 2 – 3 – 4 – 5 Acceptable 接受 – 6 – 7 – 8 – 9 – 10 Extremely acceptable 極接受

個人資料 Personal particulars

1. 性別 **Gender**	□ 男 M □ 女 F
2. 年齡 **Age**	□20 或以下 or below □ 20–29 □30–39 □40–49 □50–59 □60 或以上 or above
3. 工作狀況 **Occupation**	學生 / 在職 / 退休 / 照顧家庭，沒有工作 / 其他 (請注明) Student / Employed / Retired / Home care, not working / others Pls. specify ____________________
4. 本屋邨居民 **Resident of present Estate**	□ 是 Y □ 否 N
5. 現單位已居住年期 **Tenure (year)**	½ 或以下 or below – ½ – 1 – 1 – 3 – 3 – 5 – 5 或以上 or above
6. 住所樓層 **Floor**	□10 或以下 or below □11–20 □21–30 □31–40 □40 以上 above
7. 三十分鐘前您身處的地方是… **Where were you 30min. ago?**	□ 已經在這理 Already here □ 家中 Home □ 街市 Market □ 超級市場 Supermarket □ 商店 Shop □ 餐廳 Joint □ 街道 Street □ 交通工具 Transportation (e.g. MTR, bus etc.) □其他 (請注明) Others____________
8. 對聲音的敏感度 **Noise sensitivity**	非常不敏感 Very insensitive – 不敏感 Insensitive – 一般 Good – 敏感 Sensitive – 非常敏感 Very sensitive
9. 健康狀況 **Health condition**	非常差 Very bad – 差 Bad – 一般 Fair – 好 Good – 非常好 Very Good

The Hong Kong Polytechnic University
香港理工大學

Department of Building Environment and Energy Engineering
建築環境及能源工程學系

聲音漫步的問卷調查 Questionnaire for soundwalk

本聲音漫步為自願參與，您所提供的資料只會用作研究及發表。您的隱私權將得以保留，您的個人資料不會被公開。 This soundwalk is a voluntary. The information you provide will only be used for future research and publication. However, your privacy will be preserved, i.e. your profile will not be made public.

聲音漫步調查問卷 Soundwalk survey questionnaire (pt 1)

第1部 – 聲音環境 Acoustical environment

1. 您現在感覺到聲響有多大？ **How loud is here?**

Not at all loud 完全不大聲					Moderately loud 中等大聲					Extremely loud 極大聲
0	1	2	3	4	5	6	7	8	9	10

2. 您現在聽到以下哪些聲音？ **(可選多項)**

What can be heard at the moment? (you can tick more than one box)

- ☐ **道路交通** (汽車、貨車、巴士聲等) **Road traffic noise** (e.g. cars, trucks, buses etc.)
- ☐ **鐵路交通** (港鐵、火車聲等) **Rail traffic noise** (e.g. MTR) ☐ **人聲 Human sounds**
- ☐ **動物** (鳥鳴、蟬聲等) **Animal sounds** (e.g. birds, cicadas)
- ☐ **天然環境** (樹葉聲) **Sounds due to the elements** (e.g. leaves)
- ☐ **其他** (請注明) **Others** (pls. specify)____________________

3. **(a) 您認為哪種聲音最顯著？** (只選一項)

Which of the following types of sounds dominates? (tick only one box)

- ☐ **道路交通** (汽車、貨車、巴士聲等) **Road traffic noise** (e.g. cars, trucks, buses etc.)
- ☐ **鐵路交通** (港鐵、火車聲等) **Rail traffic noise** (e.g. MTR) ☐ **人聲 Human sounds**
- ☐ **動物** (鳥鳴、蟬聲等) **Animal sounds** (e.g. birds, cicadas)
- ☐ **天然環境** (樹葉聲) **Sounds due to the elements** (e.g. leaves)
- ☐ **其他** (請注明) **Others** (pls. specify)____________________

(b) 您現在是否看到最顯著的聲音來源？ ☐ **是 Y** ☐ **否 N**

Is the dominant sound source in sight?

第2部 – 感知的情感質量 Perceived affective quality

4. 就以下8種對目前四周聲音環境的感受，您贊同或不贊同的程度是…

For each of the eight scales below, to what extent do you agree or disagree that the present surrounding sound environment is...

	Strongly disagree 非常不同意					Neutral 中立					Strongly agree 非常同意
A. 悅耳 Pleasant	0	1	2	3	4	5	6	7	8	9	10
B. 混亂 Chaotic	0	1	2	3	4	5	6	7	8	9	10
C. 充滿生氣 Vibrant	0	1	2	3	4	5	6	7	8	9	10
D. 平淡 Uneventful	0	1	2	3	4	5	6	7	8	9	10
E. 平靜 Calm	0	1	2	3	4	5	6	7	8	9	10
F. 滋擾 Annoying	0	1	2	3	4	5	6	7	8	9	10
G. 豐富 Eventful	0	1	2	3	4	5	6	7	8	9	10
H. 單調 Monotonous	0	1	2	3	4	5	6	7	8	9	10

(pt 1)	5. 整體上您如何評價這個範圍的聲音環境？ How would you describe the overall sound environment of this area? Very bad 非常差 — Neutral 一般 — Very good 非常好 0 1 2 3 4 5 6 7 8 9 10
第3部 – **視覺環境** Visual environment	6. (a) **您認為哪種景物最顯著**？(只選一項) **Which of the following types of sounds dominates?** (tick only one box) ☐ **車路 Road** ☐ **建築物 Building** ☐ **綠化 Greenery** ☐ **天空 Sky** (b) **您**您贊同或不贊同**最顯著的景物是地標**的程度是… **To what extent do you agree the dominant landscape is a landmark?** Strongly disagree 非常不同意 — Neutral 中立 — Strongly agree 非常同意 0 1 2 3 4 5 6 7 8 9 10
	7. **您現在看到背景是…** (可選多項) **What is visually in the background?** (you can tick more than one box) ☐ **車路 Road** ☐ **建築物 Building** ☐ **綠化 Greenery** ☐ **天空 Sky** ☐ **其他** (請注明) **Others** (pls. specify)____________________________
第4部 – 目前戶外空間的聲境與景觀 Soundscape and landscape of the open space	8. 您認為現在身處的聲音環境對符合目前景觀達到怎麼樣的程度？ **To what extent is the soundscape compatible with the present landscape?** Not at all 完全不符合 — Moderately 中等符合 — Perfectly 完全符合 0 1 2 3 4 5 6 7 8 9 10 9. **您認為現在身處戶外空間的聲音環境有多大程度符合預期**？ **To what extent is the present open space sounds as you expects it to?** Not at all 完全不符合 — Moderately 中等符合 — Perfectly 完全符合 0 1 2 3 4 5 6 7 8 9 10
	10. 您如何評價您現在身處的聲音環境？ **Do you feel the present sound environment stressful or relaxing?** Very stressful 非常緊張 — Neutral 不受影響 — Very relaxing 非常放鬆 0 1 2 3 4 5 6 7 8 9 10
	11. 您如何評價您目前的景觀？ **Do you feel the present landscape stressful or relaxing?** Very stressful 非常緊張 — Neutral 不受影響 — Very relaxing 非常放鬆 0 1 2 3 4 5 6 7 8 9 10
第5部 – 大自然聲音 Natural sound preference	12. 您如何評價您對所聽到的大自然聲音？ **Please give your rating on the preference for the natural sound you just heard?**
A. 雀鳥聲音 **Birdsong**	Very much dislike 非常不喜歡 1 — Dislike 不喜歡 2 — Neutral 一般 3 — Like 喜歡 4 — Very much like 非常喜歡 5
B. 樹葉聲音 **Rattling leaves**	Very much dislike 非常不喜歡 1 — Dislike 不喜歡 2 — Neutral 一般 3 — Like 喜歡 4 — Very much like 非常喜歡 5

個人資料 Personal particulars

1. 性別 **Gender**	□ 男 M　　□ 女 F
2. 年齡 **Age**	□20 或以下 or below　□20–29　□30–39　□40–49　□50–49　□60 或以上 or above
3. 工作狀況 **Occupation**	學生 / 在職 / 退休 / 照顧家庭，沒有工作 / 其他 (請注明) Student / Employed / Retired / Home care, not working / others (pls. specify) ________________________________
4. 屋邨居民 **Resident of public Estate**	□ 是 Y　　□ 否 N
5. 現單位已居住年期 **Tenure (year)**	½ 或以下 or below　½ – 1　1 – 3　3 – 5　5 或以上 or above
6. 住所樓層 **Floor**	□10 或以下 or below　□11–20　□21–30　□31–40　□40 或以上 or above
7. 對聲音的敏感度 **Noise sensitivity**	非常不敏感 Very insensitive　不敏感 Insensitive　一般 Good　敏感 Sensitive　非常敏感 Very sensitive
8. 您的聽覺… **Is your hearing...**	Poor 差　Fair 一般　Good 好　Very Good 非常好　Excellent 極好
9. 在有背景噪音時，您有多大困難聽清楚對話？ **How much difficulty do you find in following a conversation if there is a background noise?**	No difficulty 沒有困難　Slight difficulty 少許困難　Moderate difficulty 中度困難　Great difficulty 很大困難
10. 健康狀況 **Health condition**	非常差 Very bad　差 Bad　一般 Fair　好 Good　非常好 Very Good

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