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Healthy urban blue space design: Exploring the associations of blue space quality with recreational running and cycling using crowdsourced data

Haoxiang Zhang [a], Steffen Nijhuis [a], Caroline Newton [a], Yinhua Tao [b,*]

[a] Department of Urbanism, Delft University of Technology, Delft, the Netherlands
[b] MRC Epidemiology Unit, University of Cambrdige, Cambridge, United Kingdom

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ABSTRACT

Urban blue space offers substantial health benefits by encouraging population physical activity. Despite much evidence on the nature-health nexus, the relationship between blue space and recreational exercises remains under-studied, limiting the realisation of health benefits in blue space design. Using crowdsourced data, including volunteered geographic information and street view image data, this study investigates the associations of blue space quality with recreational running and cycling in Rotterdam, the Netherlands. Results show that recreational exercise levels on street segments vary based on the blue space type and design. Compared to inland canals and rivers, small-scale recreational waterbodies are more conducive to running but not cycling, while both activities tend to cluster around the Nieuwe Maas River. Interestingly, the Water View Index shows a general negative association with both activities after adjusting for the blue space type. Besides the waterbody characteristics, eye-level environmental factors, including higher Green View Index, lower building density, more diverse land use, greater connected street network and fewer traffic elements, are associated with more running and cycling exercises. Results for visual complexity and neighbourhood population composition are mixed depending on the exercise type. These findings are further translated into spatial design patterns for developing exercise-supportive and health-promoting blue spaces.

1. Introduction

Natural environments, including green and blue spaces, provide multiple ecosystem services in urban areas (Bratman et al., 2019; Díaz et al., 2018; Tao et al., 2022). Over the past decades, the health benefits of natural environments have been widely discussed, given that the explosion of urban space takes up natural areas and poses a threat related to chronic lifestyle-related diseases (Bratman et al., 2019; Hartig & Kahn, 2016; Hartig et al., 2014). Physical activity, particularly recreational activities such as running and cycling, is considered a direct and practical approach to fulfilling the health benefits of blue or green spaces (Remme et al., 2021). An increasing number of urban planning and design concepts, such as walkability and running/cycle-friendly cities, have also emerged, emphasising the health benefits of natural environments and aiming to design exercise-supportive environments and address urban health issues (UN General Assembly, 2015).

While substantial evidence supports the green-health nexus, there is an additional need to integrate blue space into health-supportive planning measures and strategies (Hunter et al., 2023; White et al., 2020; Zhang et al., 2022). The emerging interest in the water-health relationship has been driven by some waterfront rejuvenation projects and research initiatives, such as the BlueHealth Programme, the Marine and Coastal Access Act 2009, and Blue Gym activities. (Depledge & Bird, 2009; Desfor & Jørgensen, 2004; Grellier et al., 2017; UK Government, 2009). Moreover, compared to green space, specific characteristics of the water-related environment, including the support for different types of social and physical activity and the sensory experiences with additional mental health benefits, underscore the necessity of exploring its health benefits independently. This study focused on the blue space, defined as those outdoor water-related environments - either natural or manmade - that prominently feature water and are proximally accessible to humans (Bell et al., 2021; Grellier et al., 2017; Mishra et al., 2020). We integrated multi-source data and advanced computation techniques (e.g., machine learning and computer vision techniques) to investigate the association of the spatial quality of blue spaces with recreational exercises. Following the knowledge/evidence-based design approach

* Corresponding author: MRC Epidemiology Unit, University of Cambrdige, , Full postal address: Box 285 Institute of Metabolic Science, Cambridge Biomedical Campus, Cambridge, CB2 0QQ, United Kingdom.

E-mail addresses: H.Zhang-17@tudelft.nl (H. Zhang), S.Nijhuis@tudelft.nl (S. Nijhuis), C.E.L.Newton-1@tudelft.nl (C. Newton), yh.tao@hotmail.com (Y. Tao).

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(Huang et al., 2023; Nijhuis & de Vries, 2019), we further translated our research evidence into spatial design strategies, aiming to develop exercise-friendly and health-supportive urban blue space.

1.1. A conceptual framework linking blue space, public health and spatial design

There are several established frameworks linking nature exposure and public health (Hartig et al., 2014; Markevych et al., 2017; White et al., 2020; Zhang et al., 2022). For example, Hartig et al. (2014) investigated the relationship between general natural environments and human health via four main pathways, that is, air quality, physical activity, social contact and stress reduction. Building upon this framework, Bratman et al. (2019) further examined the mental health benefits of natural environments, conceptualising it as an ecosystem service and exploring the development from evidence to application. Labib et al. (2022) concentrated on the health benefits of natural environments during pandemics, formulating targeted recommendations during crisis periods. In addition, research focusing on the distinct health effects of green and blue spaces has increasingly emerged. Markevych et al. (2017)'s research on green space refined the linkage pathways through instoration, mitigation, and restoration. White et al. (2020) and Zhang et al. (2022) applied the nature-health framework in blue space research. Specifically, White et al. (2020) incorporated modified variables, including both direct water exposure and waterfront environments, into the existing framework, while Zhang et al. (2022) extended the research framework into the planning and design practice.

Reviewing the research frameworks above, this study designed a tailored framework linking blue space with public health and extending the discussion to the practice of blue space design (Fig. 1). In the framework, exposure to blue space is the precondition for generating health benefits. Specifically, three potential pathways linking blue space exposure to health benefits are (1) mitigation, suggesting that the presence of blue spaces can enhance ambient environments and reduce health threats by regulating urban temperature (Ampatzidis & Kershaw, 2020), reducing air pollution (Ren et al., 2018), buffering traffic noise (Rådsten-Ekman et al., 2013), etc.; (2) restoration, proposing that blue spaces can decrease the risk of stress-induced diseases and enhance restoration capabilities, based on two well-known theories: Attention Restoration Theory (Kaplan & Kaplan, 1989) and Stress Reduction Theory (Ulrich et al., 1991); (3) instoration, positing that blue spaces offer ideal settings for physical and social activities (Perchoux et al., 2015; Wyles et al., 2019). Note that the three pathways are not independent but interact with each other, which exerts a joint health benefit, such as stress reduction during physical activity around blue space, i.e., the interaction between instoration and restoration pathways (Hartig et al., 2014). Subsequently, the empirical research evidence supporting the three pathways could be translated into spatial strategies or public health policies to construct sustainable healthy urban environments

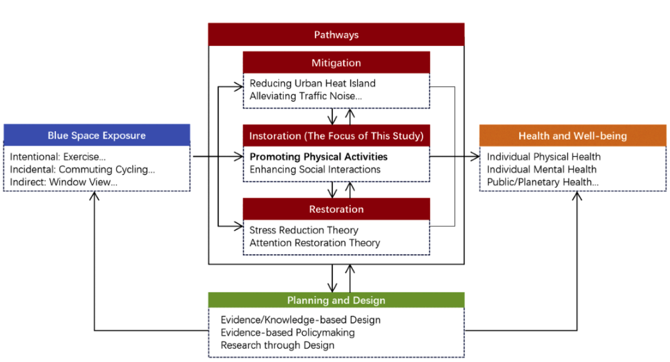

Fig. 1. A conceptual framework linking blue space, public health and spatial design.

(Brown & Corry, 2011; Nijhuis & de Vries, 2019). Following the evidence-based practice paradigm and design research approach, creative practices and applications could, in turn, be used to broaden the scope of blue space research and contribute valuable insights to in-depth health evidence.

Despite similar health benefits resulting from exposure to blue and green spaces, there are some nuanced differences in their specific pathways producing these health benefits. For instance, blue spaces contribute to reducing air pollution as wind corridors, whereas green spaces provide similar benefits, but to a lesser extent, through the tree canopy slowing down the airflow (Chen et al., 2023; Tang et al., 2023). Besides, blue spaces may provide additional stress reduction effects through unique sensory experiences from sounds and sights of water (Gidlow et al., 2016). The type of activities and their spatial requirements are also different in green and blue spaces, with blue spaces accommodating both water-based and waterfront activities.

1.2. Recreational exercises as the pathway linking blue space exposure to public health benefits

Among the aforementioned three pathways, the promotion of physical activity within the instoration pathway is one of the most effective approaches for realising the health benefits of natural environments. There are differences between blue and green spaces in promoting participation in physical activity, including: (1) blue spaces provide unique opportunities for water-based activities; (2) the duration of physical activity in blue spaces is often longer than that in green spaces (Elliott et al., 2015); (3) blue spaces confer additional mental health benefits that synergise with physical activity (Völker & Kistemann, 2013); and (4) land-based waterfront activities, such as recreational running and cycling, are also prevalent around blue spaces, while the spatial requirements for these recreational exercises may vary between green and blue spaces (Elliott et al., 2018; Pasanen et al., 2019). For these considerations, research evidence on the relationship between green spaces or general natural environments and physical activity should not be directly extrapolated to the blue-health research.

Existing blue-health research, however, often uses the measure of spatial accessibility or availability of blue space to explore its relationship with physical activity (Coombes et al., 2010; Tan et al., 2021; Tao et al., 2022). For example, studies in Australia and New Zealand found that people who lived or worked closer to blue spaces reported more frequent running and cycling activities (Murrin et al., 2023; Witten et al., 2008). Considering inconsistent evidence on the relationship between blue space accessibility and physical activities (e.g., Elliott et al., 2020; Pearson et al., 2019), researchers have realised that spatial accessibility alone is not enough to indicate individuals' usage of blue spaces (McDougall et al., 2020). More nuanced factors related to blue space quality, such as the blue space type and surrounding environmental quality, may wield significant influence over people's use of blue spaces and their willingness for physical activity participation (White et al., 2020).

There is no consensus regarding the measure of blue space quality. Previous studies have investigated how the association between blue space and recreational exercises is modified by the factors of blue space type, surrounding environmental characteristics, spatial layout or organisations of waterfront paths, and traffic conditions (McDougall et al., 2020; White et al., 2020; Zhang et al., 2023b). In these studies, experimental manipulation or on-site observation is the common approach for measuring blue space quality and inferring people's behavioural preferences and choices (Fisher et al., 2021; Higgins et al., 2019; Vert et al., 2019a, 2019b; Wilson et al., 1995; Wyles et al., 2016). Taking together the research evidence on green spaces and general built environments, we assume that spatial quality factors such as vegetation, land use mix, building density, and street connectivity may also contribute to engagement in running and cycling activities, particularly in blue spaces (Kerr et al., 2016; Ki & Lee, 2021; Liu et al., 2023; Lu, 2019; Orellana &

Guerrero, 2019; Yang et al., 2019).

Notably, previous blue-health research often uses the methods of site interviews, questionnaires or field observations to measure the spatial quality of blue space, and links it to participants' self-report or monitored intensity of overall physical activity (Akpinar, 2016; Mishra et al., 2020; Vert et al., 2019). While these traditional methods have produced insightful action-related support for spatial interventions, they also have some methodological limitations: (1) the labour-intensive and time-consuming nature of on-site observations restricts their use in large-scale research participants and research areas, showing limitations in providing evidence on the development of exercise-supportive blue spaces at a broader population/city level; (2) existing city-scale studies primarily focus on the coarse indicator of accessibility to large-scale water bodies, with little attention paid to the spatial quality of specific type of blue space; (3) the individual-level data on physical activity, whether large-scale self-reported data or experiment-based monitored data, are subject to mis-estimation on the relationship with blue space quality, due to the selection of research participants and the mis-report of physical activity (e.g., overestimation of self-reported physical activity and the short-term monitor of physical activity); (4) when investigating the relationship between blue space exposure and physical activity, previous studies often focus on a single activity type (e.g., walking) (Perchoux et al., 2015) or collectively investigating different types of physical activities (e.g. the frequency of moderate-to-strong physical activity) (Murrin et al., 2023; White et al., 2014), which underexplores unique spatial requirements associated with different types of activities.

1.3. The application of volunteered geographic information (VGI) and street view image (SVI)

With rapid development in machine learning and computer vision techniques, street view images (SVIs) are increasingly feasible to assess and evaluate health-supportive urban environments on a large spatial scale (Biljecki & Ito, 2021; Wang, 2023). SVIs create a continuous 360-degree image of urban environments, allowing researchers to understand the spatial characteristics of surrounding environments from the human eye level (Dong et al., 2023; Tang & Long, 2019). The types and quantities of elements in SVIs can be accurately recognised to measure ambient environmental characteristics, such as the green view index (GVI), the richness of public facilities, openness, complexity, etc. (Ki & Lee, 2021; Zhang et al., 2023a; Zhou et al., 2022). Regarding the measure of physical activity, the emergence of volunteer geographic information (VGI) provides a novel and practical approach to recording human behaviour in urban environments at a population level. Compared to self-reported and monitored physical activity data, VGI utilises accurate path-based behaviour data to record population distribution of physical activity in a larger spatial scale and longer time period (Huang et al., 2023). The integration of VGI and SVI data provides a good opportunity to investigate the relationship between blue space quality and physical activity participation on a large spatial scale at the population level.

Using this integrated approach, recent studies have explored how eye-level natural and street environments are associated with running activities. Dong et al. (2023) investigated the correlation between multi-scale street environment features and running behaviour in Boston. Results show that a range of environmental characteristics, encompassing natural elements, built environment components, and subjective environmental perceptions, are associated with people's propensity to engage in running. Similarly, a study in Helsinki finds that factors such as the green view index and the blue space density influence people's willingness to run (Huang et al., 2023). In contrast to emerging research on running activities, little evidence is readily available in investigating the association of eye-level environmental factors with other types of physical activity, such as cycling activities that produce at least similar health benefits but may have different spatial requirements compared to recreational running.

1.4. Knowledge gaps and research questions

There are several knowledge gaps in previous research on the relationship between blue space and physical activity. First, while the connection between green spaces or street environments and physical activity is well-studied, less is known about the relationship between blue spaces and physical activities. Despite blue spaces being considered ideal settings for such activities, there are few detailed analyses on the eye-level environmental characteristics surrounding blue spaces. Second, existing studies mainly analyse a single exercise type (e.g., running or cycling) or combine different types of exercises as a whole, which considers little the specific spatial requirement for participation in different types of exercises (e.g., an uninterrupted and smooth path for cycling and moderate view complexity for running). Third, while the integration of VGI and SVI provides methodological support for examining the relationship between environmental exposure and behavioural responses at city and population scales, it has limited application in studies related to blue spaces. Last, research evidence on the spatial patterns of physical activity needs to be translated into practical knowledge and actual actions in promoting health-supportive urban environments.

Using crowdsourced data, including the SVI data of blue spaces from Google Street Map and the VGI data of running/cycling records on the Strava platform, this study investigates the relationship between the spatial quality of blue spaces and population-level recreational exercises in Rotterdam, the Netherlands. Three research questions included in this study are: 1) How are the eye-level spatial quality factors of blue spaces, including exposure to natural and built environments, associated with running and cycling activities? 2) Do the associations between these quality factors and recreational physical activities differ between two main types of physical activities (i.e., running versus cycling), after considering the statistical distribution and spatial autocorrelation of recreational exercises? 3) Based on the answer to the above two questions, what are the key lessons in implementing exercise-friendly blue space designs and promoting evidence-based design approaches?

2. Data and methods

2.1. Study area and study design

Rotterdam, the second largest city in the Netherlands and a key European port city, is located in the province of South Holland, which has a temperate oceanic climate. It covers 326 km^2 and has a population of more than 6 million (Frantzeskaki & Tilie, 2014). As a commercial and industrial hub of the Nieuwe Maas River, Rotterdam is predominantly located on riverbanks, polders and reclaimed land. Approximately 85 % of the land lies below sea level, fostering extensive experience in water management and abundant blue space resources. Blue spaces, therefore, have become a central venue for people's daily activities. Governments have also initiated several projects to facilitate the multifunctional utilisation of blue spaces, with the city vision of 'living with water' (de Graaf & der Brugge, 2010; Dunn et al., 2017). Moreover, the cycling culture is prevalent in the Netherlands. Cycling trips account for over a quarter of the total trips for Dutch residents. Governments have also developed a comprehensive bicycle transportation network since the 1970s, with cycling lanes spanning the entire country. Cycling is regarded as a satisfactory form of daily exercise across different social groups (Fraser & Lock, 2011; Pucher & Buehler, 2008). Therefore, the selection of Rotterdam as the case will set a benchmark for developing exercise-supportive blue spaces in other cities and regions.

Fig. 2 shows the flow diagram of this study, with five steps included. First, recreational running and cycling counts at street segments around blue spaces were obtained from the Strava platform. Second, the SVIs for

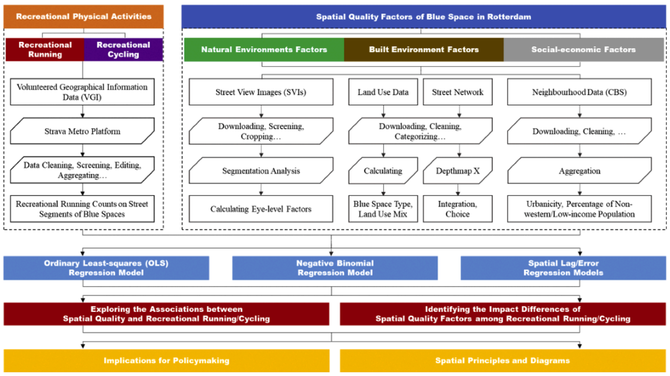

Fig. 2. The flow diagram of this study.

each sampling point on street segments of blue spaces were collected, and the pixel ratio of each eye-level spatial quality factor was calculated. Third, multi-sourced spatial quality factors relevant to running and cycling activities, including built environment, street connectivity and neighbourhood composition factors, were collected and geo-analysed. Fourth, associations of different spatial quality factors of blue spaces with physical activities were analysed, for cycling and running activities separately, by the Ordinary Least Squares (OLS) model, negative binomial (NB) model and spatial regression model. Last, tailored strategies for designing exercise-supportive and health-promoting blue spaces were developed based on the model results.

2.2. Data description

2.2.1. Dependent variables: the counts of recreational running and cycling records at street segments

The dependent variables were recreational running and cycling counts at street segments from VGI. VGI data were retrieved from the Strava platform, a GPS-based and volunteered mobile fitness application for over 100 million registered users. The representativeness of Strava data in studying public physical activity has been tested in European countries, with males and people aged 18–54 years more likely to be active users (Hochmair et al., 2019; Lee & Sener, 2021; Nelson et al., 2021; Venter et al., 2023). This study obtained the running and cycling records within the city of Rotterdam for the whole year of 2021. Given the lockdown measure during the COVID-19 pandemic, we analysed the monthly uploaded activity data on the Strava platform from 2019 to 2023, with little evidence showing annual or seasonal variations in the total numbers of activity records and active users in 2021 (see supplementary materials for detailed information). A possible reason is that governments impose little restrictions on outdoor activities throughout the pandemic. For privacy considerations, personal GPS trajectory data of running and cycling were aggregated to the street level and presented as counting numbers.

This study selected the street segments of blue spaces to investigate the associations of the spatial quality of blue spaces with recreational running and cycling separately. The selection of street segments for analysis adheres to two criteria (see supplementary materials for detailed information): (1) For planar blue spaces with distinct spatial boundaries, all roads within the blue space are included; (2) For linear blue spaces lacking distinct boundaries, a 50-meter buffer surrounding the water bodies is employed to identify target street segments, as a measure of direct exposure to blue space (Zhang et al., 2018). This resulted in a final sample of 24,050 street segments with 37,978,305 cycling records and 35,685,390 running records for the study analysis.

2.2.2. Covariates at the street segment level: spatial quality of blue spaces

The spatial quality of blue spaces was measured by exposure to four types of socio-environmental factors in blue spaces: natural environments, built environments, street connectivity and neighbourhood socio-economic composition. A description of these spatial quality factors is provided in Table 1, and more detailed algorithms for measuring each factor can be found in supplementary materials. The criteria for selecting these spatial quality factors are: (1) Some factors are drawn from research on urban green space and street environment studies, such as the Green View Index (GVI), building density, land use mix, openness, traffic elements, and socio-economic variables. (2) Spatial quality factors specific to blue spaces, including blue space type and Water View Index (WVI), are taken into account. (3) Factors relevant to the spatial pattern of recreational running and cycling, such as integration and choice of the street network, visual complexity, and urbanisation, are also included.

2.2.2.1. Spatial quality factors of natural environments. The factors of natural environments include the type of blue spaces, Water View Index (WVI), Green View Index (GVI), and openness (see supplementary materials for detailed information on the factor calculation). Based on the existing classifications of water bodies in the land use data (CBS, 2023), we categorised blue spaces into three distinct types: the Nieuwe Maas River, recreational blue spaces, and other blue spaces. The Nieuwe Maas River was treated as a separate category due to its large size and symbolic significance to Rotterdam (Rijkswaterstaat, 2023). Recreational blue spaces were those small water bodies in parks and other public recreational spaces, while the 'other blue spaces' type mainly included inland canals and rivers.

The Water View Index (WVI), Green View Index (GVI), and openness were derived through a combination of deep learning techniques and SVIs. WVI and GVI measure the proportion of water and vegetation elements (such as trees, plants and grass), and openness estimates the proportion of the sky in people's view. The calculation of these eye-level factors involves four steps (Fig. 3). First, using the Google Maps API, sampling points were generated at 30-meter intervals along each street segment, from which corresponding street view images were obtained. After inputting coordinate data of generated points and setting the capture period in a Python script, we obtained 36,970 SVIs of the size, 1500 by 750 pixels, with a 0-degree pitch angle, covering entire study street segments in Rotterdam. The sampling intervals and pitch angle selection are approximately identical to the eye-level perception of the urban environment (Jeon & Woo, 2023; Tang & Long, 2019). Second, because of the distortion of 360-degree SVIs at the edge area, we used a crop-out method to handle the distorted images. The indicators used for cropping follow the individual's field of view (FOV), including a 270-degree horizontal angle and a 150-degree vertical angle (Jeon & Woo, 2023; Ki & Lee, 2021). Subsequently, the cropped SVIs were analysed through a deep learning model, a fully conventional neural network (FCN-8 s) for semantic segmentation, to identify the features (such as water, plants and sky) within the images (Helbich et al., 2019). ADE20 K dataset, a collection of annotated images with 151 feature categories, was employed to train the model (Zhou et al., 2019). Finally, the WVI, GVI, and openness were calculated by the proportion of pixels for water, vegetation, and sky features to the total image pixels, respectively (Table 1). For each street segment, the WVI, GVI, and openness values were aggregated by the average values of these three indicators on all SVIs within that street segment.

2.2.2.2. Spatial quality factors of built environments. Built environment factors included in this study were building density, traffic elements, land use mix, and visual complexity. Using the SVI data, we measured building density by the proportion of building-related features within SVIs, which conforms more to the direct perception of building elements in surrounding environments than the widely used measure of floor area ratio. Similarly, the proportion of the elements related to traffic facilities (e.g. cars, trucks, traffic lights, etc.) in SVIs was the measure of traffic elements. Following Huang et al. (2023), this study estimated land use

Table 1
Descriptive statistics of research variables.

Dependent variable	Variable	Data time	Definition	Max.	Min.	Mean, or N	S.D., or %
Recreational Activities	Running counts	2021	The recreational running counts on the Rotterdam street segments	68,540	0	1483.8	3794.59
	Cycling counts	2021	The recreational cycling counts on the Rotterdam street segments	103,805	0	1579.2	5892.35
Spatial Quality Factors of Natural Environments	Types of blue space	2017	the Nieuwe Maas River	–	–	1211	0.05
			Recreational blue spaces	–	–	4946	0.21
			Canals, rivers and other blue spaces	–	–	17,687	0.74
	Water View Index (WVI)	2019–2020	The percentage of water bodies in SVIs $WVI = \frac{\sum_{i=1}^{n} WVI_{point-i}}{n}$; $WVI_{point-i} = \frac{Water\ pixels}{Total\ pixels} \times 100$ $WVI_{point-i}$ is the water proportion of the i_{th} street viewpoint; n is the number of street view points on the street segment	0.36	0	0.04	0.05
	Green View Index (GVI)	2019–2020	The percentage of vegetation in SVIs $GVI = \frac{\sum_{i=1}^{n} GVI_{point-i}}{n}$; $GVI_{point-i} = \frac{Vegetation\ pixels}{Total\ pixels} \times 100$ $GVI_{point-i}$ is the vegetation element proportion of the i_{th} street viewpoint; n is the number of street view points on the street segment	0.58	0	0.13	0.09
	Openness	2019–2020	The percentage of the sky in SVIs $Openness = \frac{\sum_{i=1}^{n} Openness_{point-i}}{n}$; $Openness_{point-i} = \frac{Sky\ pixels}{Total\ pixels} \times 100$ $Openness_{point-i}$ is the sky proportion of the i_{th} street viewpoint; n is the number of street view points on the street segment	0.57	0	0.33	0.09
Spatial Quality Factors of Built Environment	Building Density (BD)	2019–2020	The percentage of building elements in SVIs $BD = \frac{\sum_{i=1}^{n} BD_{point-i}}{n}$; $BD_{point-i} = \frac{Building\ element\ pixels}{Total\ pixels} \times 100$ $BD_{point-i}$ is the building element proportion of the i_{th} street viewpoint; n is the number of street view points on the street segment	0.98	0	0.51	0.27
	Land Use Mix	2017	The number of different land use types in the 100 m buffer	10	1	3.9	1.46
	Visual Complexity	2019–2020	The number of elements in SVIs with multiple thresholds (more than 0 %, 5 %, 10 % area)	59	11	27.3	3.93
	Road Traffic (RD)	2021	The percentage of traffic-related elements in SVIs $RD = \frac{\sum_{i=1}^{n} RD_{point-i}}{n}$; $RD_{point-i} = \frac{Traffic\ element\ pixels}{Total\ pixels} \times 100$ $RD_{point-i}$ is the road-traffic element proportion of the i_{th} street viewpoint; n is the number of street view points on the street segment	0.09	0	0.01	0.01
Spatial Quality Factors of Street Connectivity	Integration	2021	The proximity of each street segment to all others is based on the sum of angular changes made along each route (see supplementary for detailed information)	9025.73	0	5867.85	1197.13
	Choice	2021	The likelihood of a street segment being traversed on all shortest routes from all streets to all other streets (see supplementary for detailed information)	2.95	0	0.89	0.29
Spatial Quality Factors of Socio-economic composition	Urbanicity	2017	The urbanisation level of the neighbourhood, determined by the local ranking rules of Statistics Netherlands	5	1	1.62	1.01
	Non-western	2017	The percentage of non-western populations within the neighbourhood	0.76	0	0.30	0.16
	Low-income	2017	The percentage of the low-income population within the neighbourhood	26.4	0	9.52	5.51

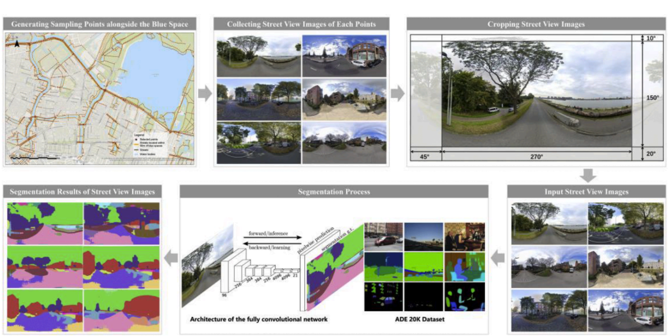

Fig. 3. The workflow of measuring eye-level spatial quality factors of blue space.

mix (LUM) by the number of different land use types in the 100 m buffer around each street segment. Land use data, retrieved from the Dutch Centraal Bureau voor de Statistiek (CBS), comprise 27 different types of land use in Rotterdam in 2017 (CBS, 2023). Visual complexity was defined by three specific metrics: the total number of elements within the SVI and the count of elements that occupy more than 5 % and 10 % of the SVI (Ode et al., 2010). These three metrics were included alternately as the factor in the following modelling analysis.

2.2.2.3. Spatial quality factors of street connectivity. Street connectivity was measured by the Space syntax, which analyses the spatial layout or properties using topological approaches and graph theory fundamentals (Hillier, 2007; Koohsari et al., 2019). Specifically, two factors based on the angular analysis of the segment-based model in Space Syntax, i.e. integration (Angular Integration) and choice (Normalised Angular Choice), were included in this study. The street integration, calculated by the sum of angular change within a certain distance threshold, represents how close each street is to others and captures the 'to-movement potential' of the street. The street choice, calculated by the number of times each segment falls on the least angular deviation path between all pairs of segments, estimates the degree to which a street segment can be passed through and measures the 'through movement potential' of the streets (van Nes & Yamu, 2017). The integration and choice values for each street segment were calculated in Depthmap X.

2.2.3. Neighbourhood composition variables: socio-economic factors

Socio-economic composition factors included urbanicity, non-western population percentage and low-income households percentage at the level of census neighbourhoods in 2021 (Buurt in Dutch). Urbanicity was measured by the density of residential populations for each neighbourhood. The non-western population percentage was assessed by the percentage of immigrants whose country of origin is from Africa, Latin America, or Asia. The percentage of low-income households was evaluated based on a fixed purchasing power level after adjusting for annual price developments (6.8 % of households at risk of poverty in 2020). Neighbourhood socio-economic information was assigned to each street segment based on the largest overlapping area with the census neighbourhoods. Neighbourhood-level socio-economic data were open-published by CBS and classified by unique census code.

2.3. Statistical analysis

Street-level running and cycling counts were separately estimated by the above four types of spatial quality factors of blue spaces. Three modelling methods, i.e., ordinary least squares (OLS), negative binomial (NB) regression, and spatial lag/error regression, were employed to evaluate the consistency of the results regarding the associations of blue space quality with recreational running and cycling (Fig. 2). OLS models were firstly fitted for easy interpretation, that is, how changes in each unit of environmental factors are associated with corresponding changes in the counts of cycling and running activities. Then, negative binomial (NB) regression models were constructed to account for the discrete measure of physical activity counts. NB regression is a generalisation of Poisson regression by relaxing its strict assumption that the variance is equal to the mean. Considering the Poisson-gamma mixture distribution, NB is appropriate to estimate the outcomes when the distribution is over-dispersed (Gardner et al., 1995). This is particularly the case for the measures of physical activity counts at the street level (Fig. 1). The OLS and NB regression models were fitted in STATA 17.

OLS and NB regression models assume spatial independence of the dependent variable and residuals. Results from the spatial autocorrelation test, however, showed that Moran's I was 0.332 ($p < 0.001$) for running and 0.241 ($p < 0.001$) for cycling. These points to a moderate-to-strong autocorrelation in the counts of physical activity and their error terms among adjacent streets. A disregard for spatial autocorrelation may overestimate the significance of the observed association. For this purpose, the spatial lag and spatial error regression models were finally fitted. Spatial lag regression posits that the value of the dependent variable in certain areas is influenced by its values in neighbouring areas, while spatial error regression operates on the premise that the error terms of the dependent variable exhibit correlation across spatial dimensions (Ward & Gleditsch, 2008). The spatial regression models were fitted in GeoDa. Note that before constructing the above models, we conducted the multicollinearity test of independent variables. The results of variance inflation factors (VIFs) were all below 4.0, indicating no serious multicollinearity issue. The dependent variables were log-transformed in OLS and spatial regression models due to the heteroskedasticity of the residuals.

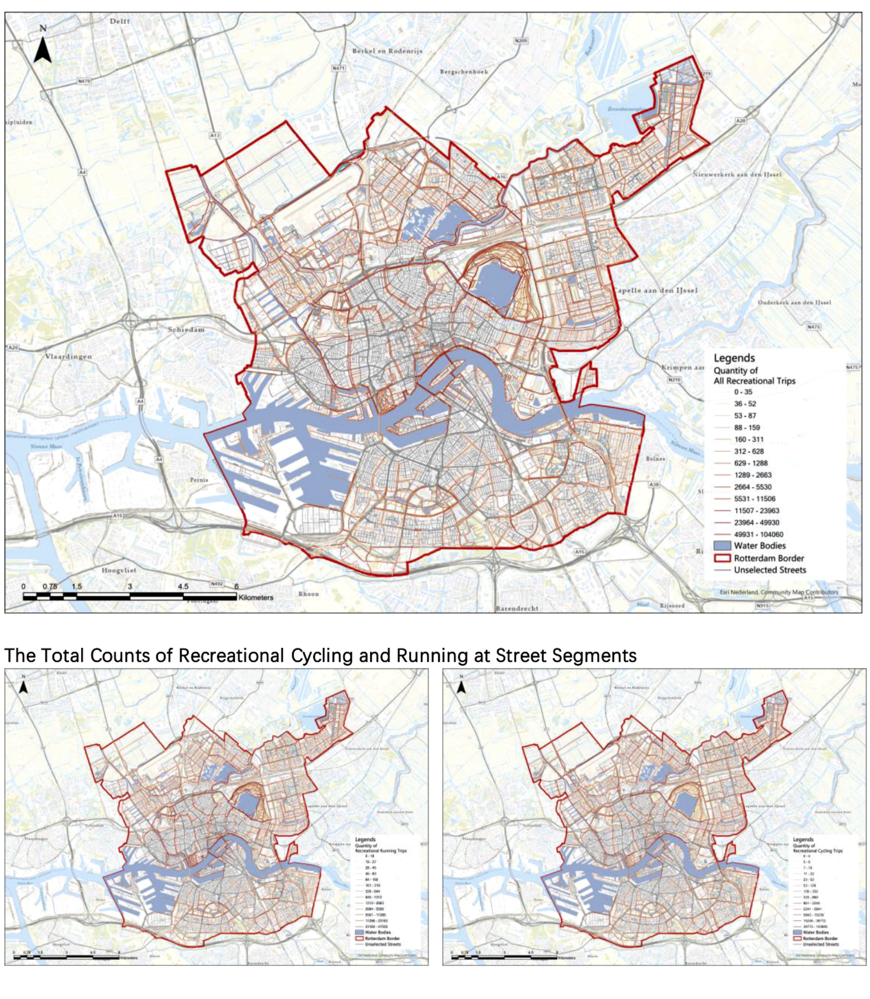

Fig. 4. The counts of recreational cycling and running at the level of street segments in Rotterdam, the Netherlands.

3. Results

3.1. Descriptive results

Table 1 shows the descriptive statistics of recreational running and cycling counts and spatial quality factors of blue spaces at the street level. 24,050 street segments located in the main urban areas of Rotterdam are included in the analysis. At the street segment level, ten spatial quality factors show great variations, and the 80 census neighbourhoods intersected with the studied street segments also vary in their socio-economic composition. Compared to running, more cycling activities are recorded across street segments (range: 0 to 103,805 for cycling versus 0 to 68,540 for running). Regarding the geographic distribution of the two activities, Fig. 4 shows cycling and running activities tend to cluster at large water bodies, such as the Nieuwe Maas River. Many runners exercise around small-scale recreational water bodies, while cyclists are widespread across inland water systems along canals and rivers.

3.2. Model results

Table 2 shows the standardised regression results for recreational running and cycling. The values of R-squared increase from Model 1 to Model 4, indicating that the overall explanatory power of the variance improves after the models take into account the statistical distribution (Model 2) and spatial dependence (Models 3 & 4) of physical activities. Note that in the spatial regression analysis, we report the model results of spatial error regression and compare the results to those of spatial lag regression, where appropriate, for two reasons. First, spatial error regression showed better model fits than spatial lag regression, based on the results for goodness-of-fit indices (spatial lag regression models: AIC = 89,264, BIC = 89,393 for running, and AIC = 100,219, BIC = 100,348 for cycling; spatial error regression models: AIC = 87,575, BIC = 87,696 for running, and AIC = 99,286, BIC = 99,405 for cycling). Second, we tested the model residuals after fitting the spatial error regression models. Results for Moran's I of residuals did not show significant spatial autocorrelation, suggesting that spatial error models performed well in controlling for the inflation of spatial autoregression and coming to more conservative estimation results (Troy et al., 2016).

3.2.1. Associations between spatial quality factors of natural environments and recreational running/cycling

Adjacent to the Nieuwe Maas River is associated with more counts of running and cycling compared to other blue spaces, including inland rivers and canals. This association shows the largest effect sizes among the spatial quality factors of natural environments across all models, except for the NB model of cycling counts. However, results for recreational blue spaces are inconsistent between the two types of activities. Compared to other blue spaces, a positive association of adjacent to recreational blue spaces is observed with running and a negative association with cycling. Interestingly, a negative correlation is found between WVI and recreational cycling, while the correlation between WVI and recreational running is insignificant in most models. To better understand the result of WVI, we refitted a Geographically Weighted Regression (GWR) model to examine the spatial heterogeneity in the association of WVI with the two activities. Results from GWR show that despite the overall negative association, a positive association between WVI and recreational exercises is observed when the exercises took place around large-scale blue spaces, such as the Nieuwe Maas River, Kralingen Lake, and Bergse Voorplas (see supplementary materials for detail). Besides the water-related environmental factors, GVI and openness are positively associated with recreational running and cycling. After accounting for the spatial autocorrelation effect, spatial regression models find that the positive association of GVI with recreational exercises increases in standardised effect size.

3.2.2. Associations between spatial quality factors of built environments and recreational running/cycling

Land use mix, building density and traffic elements exhibit consistent associations between the two activities. Specifically, building density and traffic elements negatively correlate with running and cycling, whereas land use mix demonstrates a positive correlation with the frequency of both exercises. Visual complexity is positively associated with cycling counts, while its association with running counts is insignificant after the models consider the spatial autocorrelation effect. In the sensitivity analysis, we increased the thresholds for visual complexity as the number of elements occupying more than 5 % to 10 % of the area within SVIs. After this transformation, there is a significantly positive relationship between visual complexity and running (Table 3).

3.2.3. Associations between spatial quality factors of street connectivity and recreational running/cycling

Street connectivity, especially the choice factor, is strongly predictive of both running and cycling. An increase in the choice value of street segments is associated with more counts of cycling and running at the street level. Compared to the choice factor, the integration factor is positively correlated with recreational cycling and running in a smaller effect size. Unlike the results for other spatial quality factors, the integration coefficient increases greatly after the spatial autocorrelation effect is considered in Models 3 and 4.

3.2.4. Associations between spatial quality factors of neighbourhood socio-economic composition and recreational running/cycling

Urbanicity is negatively associated with recreational cycling, indicating that more densely populated areas would discourage cycling activities. By contrast, the association between urbanicity and running is insignificant after controlling for the spatial effects. Interestingly, the non-western population percentage shows a negative correlation with running and a negligible association with cycling. A negative correlation is also observed between the low-income population percentage and two types of recreational exercises across three models.

4. Discussions

4.1. Main research findings

This study investigats the associations between spatial quality factors of blue spaces and two types of recreational physical activity for 24,050 street segments in Rotterdam, the Netherlands. The main findings are that most spatial quality factors of blue spaces on natural environments, built environments, and street connectivity are associated with recreational running and cycling, while the specific effects of spatial quality factors vary over space and show inconsistent associations between running and cycling. Nieuwe Maas River, emblematic of Rotterdam's blue space, attracts great engagement in recreational running and cycling. Besides, blue spaces with higher counts of recreational running are characterised by more recreational amenities, greater exposure to vegetation, more expansive views, lower building density, and a denser and more vibrant urban atmosphere. By contrast, an ideal blue space for recreational cycling is an environment with diverse land uses, well-connected street networks, and low population density, and similar to the results for running, people tend to cycle in a natural and open urban environment. These research findings provide evidence-based planning and design strategies for improving blue spaces suitable for recreational running/cycling and fulfilling the health benefits of blue spaces.

4.2. Interpretation of the research findings

4.2.1. Spatial quality factors of natural environments and recreational running/cycling

Recreational physical activity has specific requirements for blue space depending on the type of activities. While paths along the Nieuwe

Table 2
Model results for recreational running and cycling at the street segment level.

	Recreational Running								Recreational Cycling							
	OLS		Negative Binomial		Spatial Lag		Spatial Error		OLS		Negative Binomial		Spatial Lag		Spatial Error	
	S. Coef.	S. E.	S. Coef.	S. E.	S. Coef.	S. E.	S. Coef.	S. E.	S. Coef.	S. E.	S. Coef.	S. E.	S. Coef.	S. E.	S. Coef.	S. E.
Natural factors																
Adjacent to the inland canal	Reference		Reference		Reference		Reference		Reference		Reference		Reference		Reference	
Adjacent to the Nieuwe Maas River	0.980**	0.053	0.909**	0.045	0.631**	0.047	1.080**	0.087	0.470**	0.065	0.248**	0.060	0.379**	0.059	0.646**	0.103
Adjacent to recreational water	0.080*	0.029	0.043	0.024	0.035	0.026	0.179**	0.044	−0.658**	0.035	−0.782**	0.033	−0.367**	0.032	−0.410**	0.053
Water View Index (WVI)	−0.018	0.012	0.016	0.010	−0.009	0.011	−0.029*	0.012	−0.082**	0.015	−0.036*	0.015	−0.056**	0.014	−0.065**	0.015
Green View Index (GVI)	0.155**	0.015	0.158**	0.012	0.142**	0.013	0.222**	0.016	0.056*	0.018	0.292**	0.017	0.071**	0.017	0.115**	0.020
Openness	0.082**	0.017	0.187**	0.014	0.046**	0.014	0.064**	0.015	0.091**	0.021	0.429**	0.019	0.049**	0.017	0.048*	0.020
Built environment factors																
Building density	−0.474**	0.014	−0.592**	0.012	−0.231**	0.013	−0.201**	0.019	−0.126**	0.017	−0.116**	0.016	−0.051**	0.016	−0.044*	0.023
Land use mix	0.376**	0.012	0.308**	0.009	0.234**	0.010	0.271**	0.013	0.509**	0.014	0.668**	0.013	0.321**	0.013	0.368**	0.016
Visual complexity	0.084**	0.014	0.044**	0.011	−0.006	0.011	0.010	0.011	0.063**	0.017	0.018	0.015	0.039**	0.013	0.039**	0.014
Traffic elements	−0.096**	0.012	−0.256**	0.010	−0.052**	0.011	−0.065**	0.012	−0.116**	0.015	−0.332**	0.014	−0.069**	0.013	−0.076**	0.015
Route connectivity factors																
Choice	0.757**	0.012	0.509**	0.010	0.724**	0.011	0.739**	0.011	0.988**	0.015	0.361**	0.014	0.936**	0.014	0.923**	0.014
Integration	0.101**	0.014	−0.094*	0.012	−0.0055	0.012	0.249**	0.020	0.278**	0.017	−0.012	0.016	0.108**	0.016	0.450**	0.025
Socio-economic factors																
Urbanicity	−0.069**	0.015	−0.050**	0.013	−0.012	0.013	−0.042	0.028	−0.142**	0.019	−0.263**	0.017	−0.095**	0.017	−0.242**	0.032
Percentage of non-western population	−0.109**	0.015	−0.248**	0.013	−0.044**	0.013	−0.083**	0.029	−0.057*	0.018	−0.016	0.017	−0.025	0.017	−0.007	0.033
Percentage of low-income population	−0.172**	0.015	−0.069**	0.012	−0.093**	0.013	−0.113**	0.030	−0.132**	0.018	−0.110**	0.017	−0.084**	0.016	−0.109**	0.034
The lag or error term	—	—	—	—	0.525**	0.007	0.673**	0.007	—	—	—	—	0.476**	0.008	0.602**	0.008
(Intercept)	5.493**	0.013	6.794**	0.011	2.622**	0.041	5.484**	0.029	4.748**	0.016	7.014**	0.015	2.505**	0.040	4.728**	0.319
Model fit	R-squared	0.314	Pseudo R-squared	0.339	R-squared	0.464	R-squared	0.515	R-squared	0.311	Pseudo R-squared	0.328	R-squared	0.476	R-squared	0.457

Note: Standardised regression coefficients and standard errors are reported.
* $p < 0.05$.
** $p < 0.01$.

Table 3
Sensitivity analysis results on visual complexity.

	Cycling				Running			
	Spatial Lag		Spatial Error		Spatial Lag		Spatial Error	
	S. Coef.	S. E.	S. Coef.	S. E.	S. Coef.	S. E.	S. Coef.	S. E.
Visual complexity	0.039**	0.013	0.039**	0.014	−0.006	0.010	0.010	0.011
Visual complexity (5 %)	0.052**	0.015	0.047*	0.016	0.095**	0.012	0.072**	0.012
Visual complexity (10 %)	0.068**	0.015	0.070**	0.016	0.070**	0.012	0.059**	0.012

Note: Standardised regression coefficients and standard errors are reported.
* $p < 0.05$.
** $p < 0.01$.

Maas River are ideal for both running and cycling, small recreational water bodies cluster more running activities in the adjacent environment, and inland canals and rivers are related to more cycling exercises. This aligns with previous studies showing that large blue spaces are more attractive for health-related behaviours due to their restorative mental benefits and symbolic feeling (Murrin et al., 2023; Pasanen et al., 2019; Völker & Kistemann, 2013). When people conduct physical activity surrounding these large blue spaces, they are more likely to establish their identity and emotional attachment to the place (Völker & Kistemann, 2013). For recreational blue spaces, well-designed public and recreational facilities may enhance support for running and provide additional opportunities for social contact. For cycling, however, the presence of these facilities may disrupt the continuity of exercise, so well-developed canal and river systems, consisting of linear waterbody networks, are better suited for continuous and relatively long-distance recreational cycling in the Netherlands. Contrary to some existing evidence, this study do not find that a more eye-level water view is associated with a greater inclination for physical activity participation (Pasanen et al., 2019). Potential explanations are: (1) the flat topography in the Netherlands means that water edges are often exposed to higher wind speeds. This makes physical activity, cycling particularly, more challenging and dangerous; (2) the association between the WVI and exercises may be attenuated because the models were adjusted for the blue space type. This finding is corroborated by further GWR analysis, which demonstrates that the WVI near large-scale water bodies exhibits a positive correlation with physical activities, particularly running.

This study extends existing research evidence on the positive associations between eye-level greenness and running/cycling to the analysis in water-based environments (Chen et al., 2020; Huang et al., 2022; Ki & Lee, 2021; Lu, 2019; Lu, Yang, Sun and Gou, 2019; Nawrath et al., 2019). In blue spaces, exposure to vegetation matters for the willingness to conduct recreational running and cycling. In addition, we also find that openness is positively correlated with running and cycling. This is a valuable lesson for the spatial design of blue spaces to improve the green environment as well as to strengthen the comfort of physical activities (Dai et al., 2021; Ma et al., 2021).

4.2.2. Spatial quality factors of built environments and recreational running/cycling

Building density shows a negative correlation with both running and cycling. There are mixed findings for building density when previous studies assess it using a top-down density indicator (e.g., floor area ratio, residential building density and plot ratio) (Heinen et al., 2010; Yang et al., 2022). After separating the analysis of running and cycling, this study shows that more building elements in view significantly decrease the frequency of recreational running, while a weaker correlation is observed with less recreational cycling. The inconsistent results between running and cycling may lie in the difference in environmental perception caused by the travel speed of exercises. Compared to cycling at a higher speed, running exercises are more easily disturbed by overwhelming building elements; as a result, runners may worsen their perception of surrounding spatial quality. Besides, running routes are often set closer to the buildings than bike lanes along the blue space, resulting in more interruptions to running by the overwhelming nearby buildings.

Visual complexity is positively correlated with cycling. For running, however, we don't find a significant association with visual complexity except when the main elements of SVIs exceed a certain threshold (the element occupies more than 5 % or 10 % of the area in SVIs). According to the arousal theory, the relationship between visual complexity and people's interest in aesthetic response is not linear but shows an inverted U-shaped relationship (Berlyne, 1970; Palmer et al., 2013). Experimental studies also indicate that people prefer scenes with intermediate complexity, while a myriad of environmental elements are overwhelming to runners and increase their stress levels (Forsythe et al., 2011).

Land use mix is strongly associated with both recreational running and cycling in blue spaces, suggesting the demand for diverse land-use support (Christian et al., 2011; Huang et al., 2023; Kerr et al., 2016; Stronegger et al., 2010; Xiao et al., 2022). Particularly for cycling, there is a strong cycling tradition in the Netherlands, and cycling lanes are well-equipped in areas with diverse amenities and land functions. Moreover, the results suggest that traffic elements in view (e.g. cars, trucks, traffic lights, etc.) impose some restrictions on both recreational running and cycling. Consistent with prior research, this could result from people's concern for the safety associated with traffic elements and the potential impact of these elements on the aesthetic evaluation of space quality (Liu et al., 2023).

4.2.3. Spatial quality factors of street connectivity and recreational running/cycling

Choice and integration of the street network present strong associations with recreational running and cycling. This result aligns with previous studies showing good explanatory power of space syntax in predicting cycling and running behaviours (Koohsari et al., 2016; Orellana & Guerrero, 2019). Based on the standardised regression coefficients, the choice factor of streets has the strongest association with recreational running and cycling among all spatial quality factors. Sharmin and Kamruzzaman's (2018) review also identified the choice factor as the strongest predictor for pedestrian movements among various space syntax indicators. Regarding the variance in the impact of choice on the intensity of cycling versus running activities, a possible explanation may be that individuals prioritise route choice over exposure to natural environments when cycling (Dong et al., 2023; Jiang et al., 2022). Regarding the difference in the results between integration and choice factors, the choice focuses on the possibility of the street being traversed by people's movements, while integration emphasises the capacity to be perceived as the destination for movements (Turner, 2007; Yamu et al., 2021). Our results show that the choice can better estimate the frequency of running and cycling, possibly because recreational exercises are often discretionary without a predetermined destination.

4.2.4. Socio-economic factors and recreational running/cycling

Neighbourhood socio-economic composition is also predictive of recreational physical activities in blue spaces, which is less considered in previous research investigating the association of the environmental features of blue spaces with physical activities. Specifically, urbanicity shows negative and positive associations with recreational cycling and running, respectively. This result suggests that cycling is more likely to occur in less densely populated blue spaces, whereas running is more prevalent in densely populated locations. According to the concept of 'eyes on the street', the presence of people in public spaces can foster social cohesion and enhance safety by providing surveillance networks (Jacobs, 1961; Troy et al., 2016). Compared to cycling, perceived safety is essential for running, especially for socio-economically disadvantaged groups (Kerr et al., 2016; Li et al., 2005. Furthermore, this study finds that the non-western population percentage in the neighbourhood is negatively associated with recreational running, although no significant relations are observed for recreational cycling. Besides, street segments located in neighbourhoods with a high percentage of low-income households present a lower quantity of recreational cycling and running. Consistent with existing findings, affluent residents often live in neighbourhoods that offer high-quality blue spaces for physical activity (Huang et al., 2023; Troy et al., 2016). They also tend to possess great health awareness and are committed to regular exercise (Huang et al., 2023).

4.3. Implications for urban planning and landscape design

The research findings provide urban practitioners, including planners, designers, and policymakers, with important references for understanding the health benefits of blue spaces and developing knowledge/evidence-based spatial strategies. Based on these findings, this study proposes tailored design principles and spatial patterns of blue spaces as a demonstration of the knowledge/evidence-based design paradigm.

4.3.1. Tailor blue space design to the type of physical activity and natural environments

The planning of the running and cycling route network should align with the specific features of blue space types, such as organising cycling and running routes around emblematic blue spaces featuring large water bodies (Fig. 5[a]), coordinating running routes in conjunction with other recreational purposes in blue spaces (Fig. 5[b]) and designing cycling routes in harmony with linear blue spaces (Fig. 5[c]). Besides, street greenery is critical to recreational running and cycling. More vegetation should be introduced into blue space design, especially when designing cycling and running routes (Fig. 5[d]). Compared to the top-down measure of greenness, more attention should be paid to eye-level greenery exposure in spatial design since it is directly perceived by people and influences how people use spaces. Furthermore, expanding the visual openness of blue spaces could promote a perception of safety and increase their utilisation. The design of running and cycling areas within large-scale blue spaces should consider improving the water visibility and openness. Meanwhile, it is important to navigate the trade-offs between augmenting greenery and maintaining visual openness in blue space design, such as using strategically placed bushes or limiting canopy size to preserve openness (Fig. 5[e]).

4.3.2. Reduce building/traffic element density and avoid overwhelming visual complexity

To design exercise-supportive blue spaces, urban planners and policymakers are recommended to control the amount and layout of buildings and traffic elements around blue spaces, as well as to make full use of vegetation to obstruct buildings and traffic elements in view, such as vertical greening (Fig. 5[f]). Besides, recreational running and cycling are more likely to occur with a more diverse land use mix, which challenges improving diversity while reducing the building density. Potential strategies are providing more temporary public facilities or integrating these facilities with vegetation to minimise the negative impact of high building density (Fig. 5[g]). Moreover, our results suggest that maintaining an intermediate level of visual complexity in blue spaces could stimulate the individual's curiosity and desire for exploration, thus promoting running and cycling. Incorporating diverse landscape elements, such as various vegetation types and well-designed public facilities, could be a viable approach for designers to enhance the

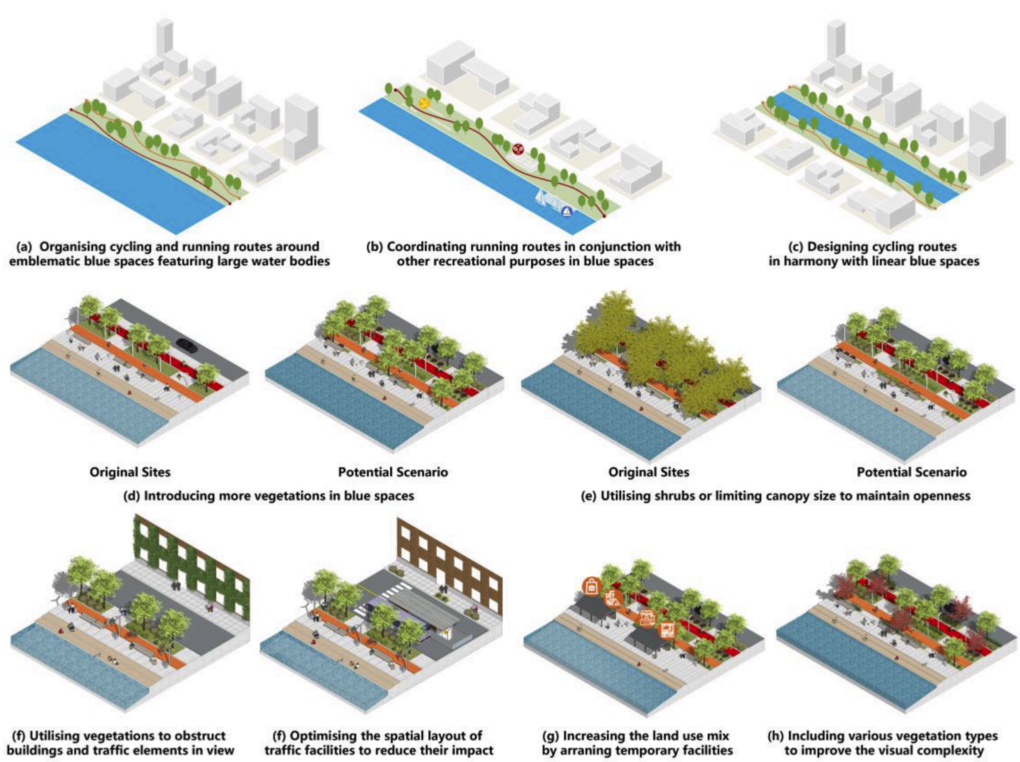

Fig. 5. Examples of spatial patterns for blue space design based on study results.

visual complexity of blue spaces (Fig. 5[h]). Notably, it is not the higher the better for visual complexity, since an over-sophisticated blue space could impede the tendency of conducting more recreational exercises.

4.3.3. Enrich the route choice for physical activity in existing street networks

Street connectivity reflects the possibility of choosing different routes for the two exercises. Although the study results show that street connectivity is significantly associated with recreational physical activities in blue spaces, the spatial interventions on adjusting street networks are always labour- and time-consuming. A potential strategy for optimising the street network is to use the highly connected streets adjacent to blue spaces as the street network skeleton and enhance the surrounding spatial quality of these streets to promote physical activities.

4.3.4. Accommodate spatial requirements for recreational exercises specific to different socio-economic contexts

Two recreational activities show spatial patterning based on the socio-economic composition of the neighbourhoods. The potential challenge lies in the limited availability and poor maintenance of running and cycling facilities in neighbourhoods with a concentration of ethnic minority groups and low-income people. Planners and policymakers should prioritise the equitable distribution of high-quality blue spaces, particularly in ethnic minority and low-income neighbourhoods. Besides, the design of running and cycling facilities needs to account for the population density of neighbourhoods. Blue spaces in highly populated areas should place more running facilities and connect running routes with existing street networks, promoting interaction with other public facilities and improving accessibility to surrounding neighbourhoods. More developed cycling-related facilities are also required in blue spaces with less urbanised levels.

4.3.5. Leverage the synergy and trade-offs among the design principles and patterns of blue space

Researchers, urban planners and policymakers should consider the synergies and trade-offs between the spatial strategies. For instance, when designing blue spaces for running, the LUM can be improved by creating mixed land-use functions, as well as by increasing the urbanicity to attract more eyes to the street. Blue spaces with good street connectivity tend to have a higher building density in view; therefore, it is necessary to balance these two factors in practice or implement other strategies to mediate the negative effects, such as the aforementioned vertical greening. Additionally, it is essential to recognise the synergistic relationships between existing design strategies and increasing research evidence. Prior research highlights the importance of enhancing the spatial accessibility to blue spaces as a way to stimulate physical activity participation, which leads to the prevalence of route network planning in blue spaces. With emerging research evidence introduced, such as the varying spatial requirements between cycling and running activities, as found in this study, practitioners should update their evidence-based knowledge to design waterfront environments specific to the type of blue spaces and physical activity.

4.4. Strengths and limitations

This study is one of the first citywide studies to assess the associations between the spatial quality of blue spaces and two recreational physical activities, including running and cycling. We have integrated multi-source data to identify the nuanced spatial quality of blue spaces, together with a GPS-based VGI approach to measure physical activities throughout the year at the street level. Particularly, the eye-level element proportions through SVIs and deep learning techniques are more representative of people's experience in reality than traditional top-down measurement relying on land use data. In addition, statistical and spatial regression models are used in this study to control for the distributional characteristics and spatial autocorrelation of the research outcome, i.e., recreational running and cycling counts. Based on the knowledge/evidence-based design paradigm, our study further provides implications for urban practitioners in developing exercise-supportive and health-promoting blue spaces.

This study also has some limitations. First, the crowdsourced data on physical activity are subject to potential bias from sample selection, despite the advantage of population-level data over a great spatiotemporal scale. On the Strava platform, the registered users are over-representation of males, young-to-middle-aged adults and active athletes (Hochmair et al., 2019; Lee & Sener, 2021; Nelson et al., 2021; Venter et al., 2023). Besides, research evidence in the Netherlands, which has a strong cycling culture, well-developed cycling infrastructure and long-term water management experience, may not be directly generalised to other cities and regions. Therefore, we welcome future research to validate our findings using other data sources, especially among underrepresented social groups (e.g., females, old people and people with illness) who are faced with more serious health risks, and in other cases, areas where the enhancement of blue spaces can be regarded a promising approach to encourage daily exercises among the public.

Second, this study investigated the associations of natural, built, and street environments with recreational exercises after accounting for neighbourhood socio-economic contexts. Even so, unobserved confounders, including availability of recreational facilities, characteristics of running/cycling routes, weather conditions and seasonal variations, are still an unresolved issue for further discussion. Moreover, given the street-level data used, this study is unlikely to elucidate the individual-level pathway underlying the environmental determinants of physical activity. Traditional questionnaire surveys and qualitative research, as well as some innovative human-machine adversarial models, are important supplementary methods. Research on people's subjective evaluation of water-related environments (e.g., safety, liveliness and aesthetics) is particularly relevant to understanding their perception of blue spaces and willingness for physical activity participation.

Third, the measurement of eye-level environmental factors in this research relies on the proportion and quantity of selected elements within the view. This leaves the organisational characteristics of these elements (i.e. spaces with identical GVI could present varied spatial atmospheres) less considered. New datasets, machine learning models, and additional data (i.e., point cloud data) are needed to comprehensively assess spatial organisational characteristics and their relationship with physical activity. When more spatial data are included in the analysis, the modelling methods should carefully consider their heterogeneous associations with behavioural outcomes over space. This research focuses on the general associations between blue space quality and physical activities at the urban scale, with spatial heterogeneity analysed to a limited extent in interpreting the result for WVI. More sophisticated geospatial models, such as mixed-effect GWR, generalised additive models, and random forest regression, are readily available to predict the occurrence of physical activity more accurately over space and time.

5. Conclusions

Integrating crowdsourced data of volunteered geographic information (VGI) and street view images (SVIs), this study investigates the relationship between the spatial quality of blue spaces and the amount of recreational running/cycling in Rotterdam, the Netherlands. The results indicate that GVI and openness ware positively associated with both cycling and running in blue spaces, while WVI shows an overall negative association with recreational exercises after adjusting for different types of blue spaces. Furthermore, the increased LUM in the surrounding areas, coupled with lower building density and traffic elements at eye level, are associated with more recreational exercises. A moderate level of visual complexity is more conducive to running than cycling, whereas streets with a greater likelihood of being traversed in the street network show the strongest association with more recreational exercises among all spatial quality factors. These findings not only contribute to blue-health research by examining the relationship between blue space quality and recreational exercises, but also provide robust evidence for planners and policymakers regarding how to construct exercise-friendly and health-promoting blue spaces.

Notes on contributors

Haoxiang ZHANG is a PhD candidate in the Department of Urbanism at the Faculty of Architecture and the Built Environment, Delft University of Technology (the Netherlands). Email: H.Zhang-17@tudelft.nl

Steffen NIJHUIS is the Professor of Landscape-based Urbanism and Head of the Section of Landscape Architecture at the Faculty of Architecture and the Built Environment, Delft University of Technology (the Netherlands). Email: S.Nijhuis@tudelft.nl

Caroline NEWTON is an Associate Professor and Van Eesteren Fellow in the Department of Urbanism at the Faculty of Architecture and the Built Environment, Delft University of Technology (the Netherlands). Email: C.E.L.Newton-1@tudelft.nl

Yinhua TAO is a Postdoctoral Rsearch Associate at the MRC Epidemiology Unit, University of Cambridge (United Kingdom). Email: yh.tao@hotmail.com.

CRediT authorship contribution statement

Haoxiang Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Steffen Nijhuis:** Writing – review & editing, Supervision, Project administration, Investigation, Conceptualization. **Caroline Newton:** Writing – review & editing, Supervision, Project administration, Investigation, Conceptualization. **Yinhua Tao:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2024.105929.

Data availability

Data will be made available on request.

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