Features of the Neighbourhood Built Environment and Their Ability to Predict Fitness in Youth: A Random Forest Approach

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ABSTRACT

Background: Cardiorespiratory Fitness (CRF) is an important marker of health among youth, strongly linked to improved cardiometabolic outcomes and reduced risk of early-onset cardiovascular disease. Factors at the individual, behavioural, and environmental levels are all implicated in shaping CRF. Notably, favourable Neighbourhood Built Environment (NBE) features are generally recognized as supportive of physical activity and active living; however, the nature of specific features, and the magnitude of their potential contribution to CRF in youth, require further investigation.

Objectives: The primary objective of this thesis was to estimate the extent to which NBE features predict CRF in youth. A supplementary analysis examined gender-specific differences in the associations between NBE features and predicted CRF using stratified analyses.

Methods: This study used data from the Quebec Adipose and Lifestyle InvesTigation in Youth (QUALITY) cohort. The QUALITY cohort comprised 630 families, including a child aged 8–10 years at baseline, and both biological parents, with at least one parent living with obesity. Data included those collecting during the initial (baseline) visit, and analyses were restricted to participants in the Greater Montreal Area (n = 504). CRF was assessed using peak oxygen volume consumption (VO2peak) during a cycling test on an electromagnetic bike, adjusted for Fat-Free Mass (FFM) as measured by DXA, and expressed as VO2peak/FFM ($mL \cdot min^{-1} \cdot kg^{-1}$ FFM). Moderate to vigorous physical activity was measured using a uniaxial accelerometer worn for 7 days, with valid wear time defined as a minimum of 10 hours per day on at least 3 weekdays and 1 weekend day. Salient NBE features were captured through a Geographic Information System (GIS) and on-site audits. Random forest models were applied to examine the predictive capability of NBE features in relation to VO2peak/FFM as a proxy for CRF. Bivariate associations between predictors and predicted CRF were visualized using scatter plots and violin plots, for the full dataset, and stratified by gender.

Results: Among 504 children (mean age 9.6 ± 0.9 years; 54% boys) boys exhibited higher mean VO2peak/FFM (71.2 $min^{-1} \cdot kg\ FFM^{-1}$, SD = 13.8) compared to girls (63.4 $min^{-1} \cdot kg\ FFM^{-1}$, SD = 11.4). The random forest model explained 33% of the variance in CRF, with BMI z-score, sex, and moderate to vigorous physical activity emerging as the top three predictors, followed by several NBE features, including the density of streets with normal traffic, number of intersections, vegetation index (NDVI), land use mix, building density, and signs of social disorder. Sex-specific analyses point to potential gendered-patterns: a modest positive association was observed between NDVI and predicted CRF, while nonlinear trends between number of intersections, land use mix, and predicted CRF among boys; in contrast, associations were largely negligible among girls.

Conclusion: This study identified several NBE features with a moderate to weak contribution in predicting CRF, in addition to established sociodemographic factors and levels of physical activity. While the contributions of NBE features were relatively modest, they suggest potential for targets for neighbourhood transformations that may foster healthier lifestyles and improve CRF in youth populations. These findings could be useful to inform urban planning and public health research and policies, and should be extended to address the specific needs of diverse populations more broadly.

RÉSUMÉ

Contexte : La condition physique cardiorespiratoire (CPC) est un indicateur important de la santé chez les jeunes, fortement associée à une amélioration des résultats cardiométaboliques et à une réduction du risque de maladies cardiovasculaires précoces. L’interaction entre les facteurs individuels, comportementaux et environnementaux peut influencer la CPC. Parmi ces facteurs, l’environnement bâti du quartier (EBQ) est reconnu pour soutenir l’activité physique ; toutefois, sa contribution spécifique à la CPC chez les jeunes nécessite une investigation approfondie.

Objectifs : L’objectif principal de cette thèse est d’estimer dans quelle mesure les différentes caractéristiques de l’EBQ prédisent la CPC chez les jeunes. Une analyse supplémentaire fut menée pour explorer les différences liées au sexe dans les associations entre les caractéristiques de l’EBQ et la CPC prédite au moyen d’analyses stratifiées.

Méthodes : Cette étude a utilisé les données de la cohorte QUALITY (Quebec Adipose and Lifestyle InvesTigation in Youth), qui inclut 630 enfants âgés de 8 à 10 ans au départ, ayant au moins un parent biologique vivant avec l’obésité. Les analyses ont été limitées aux participants de la région du Grand Montréal (n = 504) lors de la visite de base. La CPC a été évaluée à l’aide de la consommation maximale d’oxygène (VO2peak) mesurée lors d’un test de cyclisme sur un vélo électromagnétique, ajustée pour la masse maigre (FFM) mesurée par DXA. <L’APMV a été mesurée objectivement à l’aide d’accéléromètres. Les caractéristiques importantes de l’EBQ ont été recueillies à l’aide de systèmes d’information géographique (SIG) et d’observation systématique des tronçons. Des modèles de forêts aléatoires ont été appliqués pour examiner la capacité prédictive de ces caractéristiques en relation avec le VO2peak/FFM, utilisé comme proxy pour la CPC. Les associations bivariées entre les prédicteurs et la CPC prédite ont été visualisées

à l'aide de diagrammes de dispersion et de graphiques en violon pour l'ensemble des données et pour les données stratifiées par sexe.

Résultats : Les garçons ont démontré une moyenne de VO2peak/FFM plus élevée (71.2 $min^{-1} \cdot kg\ FFM^{-1}$, SD = 13.8) par rapport aux filles (63.4 $min^{-1} \cdot kg\ FFM^{-1}$, SD = 11.4). Les modèles de forêts aléatoires ont expliqué 33 % de la variance de la CPC, avec le score-z de l'IMC, le sexe et l'APMV identifiés comme étant les trois principaux prédicteurs, suivis par les caractéristiques de l'EBQ, notamment la densité trafic normal, le nombre d'intersections, l'indice de végétation normalisé (NDVI), la mixité des usages des sols, la densité des bâtiments et le désordre social. L'analyse stratifiée par sexe a suggéré des tendances potentiellement spécifiques au genre. Une association positive modeste a été observée entre le NDVI et la CPC prédite, avec des tendances non linéaires entre le nombre d'intersections, la mixité des usages des sols et la CPC prédite chez les garçons. En revanche, ces prédicteurs montrent des associations minimales ou négligeables chez les filles, comme l'indiquent des tendances plates et des bandes de confiance qui se chevauchent dans la plupart des cas.

Conclusion : Cette étude a identifié plusieurs caractéristiques de l'EBQ ayant une contribution modérée à faible dans la prédiction de la CPC, en plus des facteurs sociodémographiques établis et de l'activité physique. Ces résultats suggèrent que des stratégies visant à modifier les environnements bâtis pourraient contribuer à améliorer la CPC chez les jeunes.

List of Abbreviations

BMI - Body Mass Index

BMI z-score - Standardized Body Mass Index

CANUE - Canadian Urban Environmental Health Research Consortium

CFPC - College of Family Physicians of Canada

CRF - Cardiorespiratory Fitness

DAG - Directed Acyclic Graph

DXA - Dual-Energy X-ray Absorptiometry

FFM - Fat-Free Mass

GIS - Geographic Information System

MVPA - Moderate to Vigorous Physical Activity

NBE - Neighbourhood Built Environment

NDVI - Normalized Difference Vegetation Index

NEWS - Neighbourhood Environment Walkability Scale

PACER - Progressive Aerobic Cardiovascular Endurance Run

PM2.5 - Fine Particulate Matter (Particulate Matter ≤ 2.5 μm)

PMH - Patient's Medical Home

RER - Respiratory Exchange Ratio

SD - Standard Deviation

SES - Socioeconomic Status

VO2peak - Peak Oxygen Consumption

VO2peak/FFM - Peak Oxygen Consumption Adjusted for Fat-Free Mass

VO2max - Maximum Oxygen Consumption

%IncMSE - Increase in Mean-squared Error

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This thesis is dedicated to the memory of my uncle, Dr. Mahdi Salimi.

Preface

Format of the thesis: This thesis follows a manuscript-based format.

Contribution of authors

As an MSc student and the first author of the enclosed manuscript, Dorsa Salimi participated in all aspects of the study. She developed the project idea and performed all data preparation, analysis and programming, and drafted the manuscript and this thesis.

Dr. Tracie Barnett, as the primary supervisor, assisted in the development of the project idea , provided input on data analysis and interpretation, and provided multiple rounds of feedback on the draft of the manuscript and of the thesis.

Dr. Tibor Schuster, as a close collaborator, assisted with all aspects of data preparation and analysis. He assisted with validation of the code used in the analysis and aided with the preparation of visuals and with the interpretation of results.

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Dr. Andraea Van Hulst assisted with the development of the project idea and provided valuable feedback on the proposed investigation as well as on the final draft of the manuscript.

Dr. Melanie Henderson is the principal investigator on the QUALITY study project. She provided input on the development of the project idea.

CHAPTER 1: INTRODUCTION

Non-communicable diseases are responsible for an estimated 35 million death annually, with cardiovascular disease accounting for 30% of global mortality (1). Cardiorespiratory Fitness (CRF), defined as the capacity of the circulatory and respiratory systems to supply oxygen for energy production, is a strong and independent predictor of both cardiovascular disease and all-cause mortality in adults (2). Among youth, CRF is an important indicator of health outcomes, including cardiometabolic health and early-onset cardiovascular disease (3). Additionally, CRF is associated with improved mental health, reducing the risks of depression and anxiety while boosting mood and self-esteem, and positively correlating with cognitive function and academic achievement (4–7).

Over the past decades, CRF has declined among children globally (8,9). While genetics establish individual CRF to a large extent, behavioural and environmental factors also play significant roles. In particular, changes in social and built environment over the past decades, such as increased traffic density, reduced green spaces, and increased concerns about safety, accompanied by rising obesity rates, have likely conspired to lead to and could be linked to declines in CRF (10–13). For instance, only 40% of Canadian youth aged 5 to 17 years achieve the WHO recommended 60 minutes of moderate to vigorous physical activity (MVPA) per day, with a notable gender disparity, as girls are half as likely as boys to meet this target (26% vs. 52%) (15).

The evidence suggests the Neighbourhood Built Environment (NBE) plays a critical role in shaping opportunities for regular physical activity, particularly through features such as walkability and local amenities and installations (17). Unlike factors such as genetic predispositions, individual lifestyle behaviours and the built environment are modifiable determinants of health that can be improved through urban planning, policy interventions, and subsequent behaviour modification. By understanding which specific features of the built environment influence CRF, public health practitioners, urban planners, and policy makers may be better equipped to transform and design neighbourhoods that promote active living.

The relationship between the NBE and CRF in children and adolescents has been explored in a limited number of studies, with mixed findings. Positive associations have been reported for walkability infrastructure (e.g., street connectivity, walking and bicycling routes), green spaces, and outdoor fields(17–19). In contrast, negative associations have been reported for heavy traffic and distance to recreational facilities (19,20). Null or inconsistent associations have been noted for features related to neighbourhood density, diversity and desirability (21,22). Neighbourhoods are inherently multidimensional systems and built environment features tend to be intercorrelated (23). Consequently, modelling their relationship with health outcomes requires approaches that account for their interconnected nature. However, much of the existing research focuses on single environmental characteristics, studied in isolation, using analyses that fail to address multicollinearity or allow for potential nonlinear associations.

This study examined how NBE features are associated with CRF in children and adolescents using random forest, a supervised machine learning method designed to handle multicollinearity and to capture nonlinear relationships. The evidence and insights could be valuable for urban planners, public health officials, and other interest holders who strive to foster healthy, active lifestyles among youth.

1.1 Objectives

The primary objective of this thesis was to estimate the extent to which a range of NBE features predict CRF in children and adolescents. This objective is pursued in Chapter 3 (manuscript). In supplementary analyses, I examined whether the associations between NBE features and predicted CRF differed by gender, in sex-specific analyses.

1.2 Thesis Structure Overview

Following a brief introductory chapter, Chapter 2 comprises a review of the existing literature on the NBE and CRF. Chapter 3 comprises the manuscript, addressing the primary objective of the study. Chapter 4 includes supplementary analyses not included in the manuscript (due to journal word count restrictions). Finally, Chapter 5 concludes the thesis with a discussion of the findings, their significance in family medicine, and potential directions for future research.

CHAPTER 2. LITERATURE REVIEW

2.1 CRF: a Critical Component of Physical Fitness

Physical fitness is a multicomponent construct characterized by the capacity to perform daily tasks with energy (7). It encompasses various physiological attributes that reduce the risk of developing hypokinetic diseases and enhance overall health (24,25). These attributes include muscular, morphological, motor and CRF (25). CRF indicates the efficiency of the cardiovascular and respiratory systems in supplying oxygen to the muscles during sustained physical activity (26). CRF is often highlighted as a critical component of physical fitness due to its strong association with health outcomes (27). A direct inverse correlation exists between CRF in youth and all-cause mortality, including cardiovascular diseases, across the life span (28). In addition to reducing the risks of conditions like metabolic syndrome and type 2 diabetes, CRF supports mental well-being by mitigating depression and anxiety, enhancing self-esteem, and improving cognitive function and academic performance (2,19,20).

2.1.1 Declining Trends in CRF Among Youth

CRF among youth has significantly declined over the past few decades (8). Tomkinson et al. analyzed data from 137 studies, encompassing 965,264 children and adolescents aged 9 to 17 years across 19 countries, and estimated that CRF decreased by more than 7% over a 33-year period from 1981 to 2014 (9). The study conducted in Québec, Canada, examined secular trends in CRF among 3,128 youth using the 20-m shuttle run test. Since 1980s, CRF has declined significantly, with a 30% reduction in VO2 max values and shuttle run stages completed (31).

2.1.2 CRF Predictors: Biological, Behavioral, and Environmental Factors

Non-modifiable and modifiable factors, including genetics, age, sex, physical activity, dietary patterns, body composition, sedentary behaviour, the built environment, and socioeconomic status, can shape variations in CRF (32). Genetics play a substantial role in influencing an individual's CRF, with heritability estimates for maximal oxygen uptake (VO2max) ranging from 54% to 87% in different age groups (33). However, the specific genes responsible for differences in CRF between individuals have not been identified (34).

Age and sex are key determinants of CRF (35). During childhood and adolescence, CRF generally improves due to physical growth and maturation, including increases in muscle mass and aerobic capacity (36). A study by Guimarães et al. on the QUALITY cohort found that while both boys and girls show age-related increases in peak VO2, sex differences emerge, with boys consistently achieve higher levels in both absolute and relative terms (37). These differences are largely explained by sex-specific factors (38,39). Girls experience earlier pubertal onset, consequently higher body fat percentage, which is negatively associated with CRF (40). In contrast, boys maintain greater lean muscle mass and engage in higher-intensity physical activities, which contribute significantly to their higher CRF levels (40). Additionally, boys generally have higher hemoglobin concentrations and larger cardiac dimensions, which enhance oxygen-carrying capacity and cardiac output during exercise (36).

Body composition is closely associated with CRF, as factors like muscle mass and fat distribution influence fitness levels (43). Excess body weight, particularly obesity, is linked to lower CRF, emphasizing the importance of maintaining a healthy weight through a balanced diet and regular exercise (44,45). Physical activity, particularly vigorous activity, plays a significant role in enhancing CRF (46). High levels of sedentary behaviour can be negatively associated with CRF, although the relationship may be influenced or attenuated by overall physical activity levels (48). Socioeconomic status and environmental factors are also associated with CRF, with disparities often resulting in lower CRF levels in youth from urban and low-income settings (49). These diverse predictors highlight the complex interplay of biological, behavioural, and environmental influences on CRF in youth (50).

2.1.3 Challenges and Advances in Measuring CRF Among Youth

Measuring CRF in youth is a complex process requiring careful consideration of various physiological and developmental factors. The gold standard of CRF measurement is the determination of VO2 max, representing the maximum oxygen consumption rate during intense exercise involving large muscle groups (51,52). However, the term VO2 peak is used instead of

VO2 max in children and adolescents because these populations often do not exhibit a plateau in their oxygen uptake curve during incremental exercise. To ensure accurate peak oxygen uptake ($\dot{V}O2$) measurements in youth assessing CRF, alongside subjective signs of effort (e.g., facial flushing, sweating), secondary criteria such as Respiratory Exchange Ratio (RER) exceeds 1.0, heart rate thresholds (typically 85% of age-predicted maximum), and blood lactate levels are commonly employed to confirm a maximal response (53).

VO2 peak is the most reliable way of measuring aerobic fitness in children and adolescents, comprehensively evaluating their cardiorespiratory capacity (54). However, it should be noted that the accuracy of these secondary criteria in children shows variability, with wide interindividual ranges reported in RER (0.95–1.15), heart rate (185–215 beats/min), and blood lactate (3–12 mM) at exhaustion (55). Relying on these secondary criteria may result in the acceptance of submaximal $\dot{V}O2$ values or the rejection of true maximal values, potentially leading to underestimations ranging from 10% to 22% (55,56).

Moreover, interpreting $\dot{V}O2$ values requires consideration for differences in sex, age, body mass, fat-free mass (FFM), and maturity status (57). Boys typically exhibit a near-linear increase in absolute peak $\dot{V}O2$ with age, whereas girls' values tend to plateau during mid to late adolescence (36). Adjusting $\dot{V}O2$ for body mass yields a more accurate representation by considering the differential impact of body size. However, this traditional ratio scaling of $\dot{V}O2$ to body mass (expressed as mL·kg−1·min−1) has limitations, as it does not adequately adjust for body composition differences and can misclassify overweight or more mature youth as less fit (58). Longitudinal studies utilizing the advanced scaling methods highlight the significant influence of maturational changes in FFM on CRF. Therefore, robust assessment of CRF in youth should employ sophisticated scaling techniques that account for these critical variables to ensure accurate and meaningful evaluations of aerobic fitness (59).

2.2 Built Environment Definition

The built environment refers to the human-made physical surroundings that shape daily life, including where people live, work, learn, and engage in recreational activities (16,60,61). The NBE may be particularly influential on physical health and well-being, as it is thought to directly shape the settings in which people carry out their daily activities and interactions. To better understand the characteristics of such environments, Giles-Corti et al. outlined a framework emphasizing urban features that promote compact and walkable cities (62). Informed by this framework, this study focuses on specific local urban features, including design (connected street networks and public spaces to support safe and convenient pedestrian, cycling, and transit access), density (high residential densities to support local businesses and efficient public transport) diversity (a mix of housing, commercial, and recreational spaces within neighbourhoods), and desirability (safe, attractive, and comfortable neighbourhoods with greening and crime prevention measures) (62,63).

2.2.1 Measuring the Built Environments

The built environment can be assessed through various methods, including resident perceptions, systematic social observation, and geographic information systems (GIS) (64). Resident perceptions, often self-reported, provide insights into individuals' impressions of their surroundings, capturing more qualitative elements such as perceived safety, aesthetics, and social trust, in addition to access and quality of services and infrastructure. Systematic social observation involves trained research assistants who observe and record specific tangible (e.g. presence of crosswalks) and intangible (e.g. curb appeal) neighbourhood characteristics (65). GIS-based approaches utilize large data sets of geo-located variables, such as destinations, road networks, and census-based information, generating compositional or aggregated characteristics of neighbourhoods (66). By combining multiple measurement methods, researchers can gain a more comprehensive and nuanced understanding of how the built environment may affect health behaviours and outcomes.

2.2.2 Neighbourhood Built Environment and Physical Activity

Understanding how individuals interact with and are affected by their surroundings has become a key focus in studying human health (67). There is substantial evidence that various neighbourhood features influence a range of behavioural and health outcomes in children, youth, and adults (16,68). Walkable neighbourhoods, characterized by features such as sidewalks, trails, a variety of destinations in close proximity, perceived safety, etc., are linked to higher levels of physical activity and improved mental health outcomes (69,70). Neighbourhood safety, connectivity, and the presence of diverse destinations significantly promote active lifestyles (71,72). For children and adolescents, key environmental factors that encourage physical activity include walkability, traffic speed and volume, access and proximity to recreation facilities, land use mix, and residential density (73,74). Conversely, living in neighbourhoods with signs of social disorder and that are perceived to be less safe is associated with reduced physical activity and higher likelihood of obesity and depression among children and adolescents (75,76). Well-designed pedestrian pathways and reduced traffic exposure encourage walking and outdoor play, which may be of particular benefit to younger children (66,77).

2.2.3 Neighbourhood Built Environment and Fitness

To identify the relevant literature, an extensive search was conducted on SportDiscus (Ebsco), Medline (OVID), and Web of Science using a combination of index terms with unique subject headings and keywords related to NBE, CRF and pediatric populations. Nine studies were retained, with details provided in Tables 2.1 and 2.2.

CRF was measured by the 20-meter shuttle run, in four studies, a progressive aerobic endurance test requiring participants to run back and forth over 20 meters at increasing speeds until exhaustion (18–20,78). The Progressive Aerobic Cardiovascular Endurance Run (PACER) test, utilized in two studies, is a multistage shuttle run that measures aerobic capacity through progressively faster intervals (17,21). The PWC170 VO2 max test assesses aerobic fitness by measuring power output at a heart rate of 170 bpm during cycling (79). The Cooper Run Test evaluates aerobic fitness by measuring the distance covered in a 12-minute run (22), while the YMCA Step Test gauges cardiovascular endurance by assessing recovery heart rate after a 3-minute stepping exercise (80). NBE features were assessed through different methods, including GIS, audits, census data, and self-report questionnaires, such as the Neighbourhood Environment Walkability Scale (NEWS-Y). Regarding covariates, all studies included sex, seven accounted for age, and seven considered socioeconomic status (SES) using various proxies. Only two studies considered MVPA; these two studies treated MVPA as a confounder in the regression models, reporting that observed associations (between the NBE and CRF) persisted even after adjusting for MVPA (19,80).

In a cross-sectional study involving 3,528 youth from European cities, Vanhels et al. reported that secure walking and bicycling routes, outdoor fields, and shops near home were significantly associated with higher CRF, while living in neighbourhoods with heavy traffic was associated with lower CRF (19). Similarly, Michaela James et al. emphasized the positive impact of green spaces on adolescent physical activity levels and overall fitness (22). Two studies from the Fit2Play project provide valuable insights into the relationship between multiple indicators of neighbourhood quality, as measured by the Child Opportunity Index (COI), and youth fitness. The first, a cross-sectional study by Zewdie et al., assessed neighbourhood features such as walkability, greenspace, access to healthy foods, and commute duration. While walkability was associated with lower BMI and diastolic blood pressure, no significant associations were reported between neighbourhood features and CRF, measured by the PACER test (21). In contrast, the second, a longitudinal study by Zewdie et al., reported that the Child Opportunity Index (COI) was associated with improved aerobic capacity, with neighbourhood indicators such as greenspace, walkability, and commute duration showing positive associations with CRF and other fitness metrics over time (17).

A cohort study by Oliveira et al. reported that greater distance to local recreational facilities was associated with lower CRF (20). A study by Pitts et al. reported that higher neighbourhood amenity density, as measured by Walk Score, was associated with greater lower CRF, and reduced MVPA among urban youth (80). The authors explained these unexpected findings by highlighting a correlation between Walk Score and crime in these neighbourhoods, suggesting that other factors, such as neighbourhood safety or infrastructure quality, may play a role in mitigating the expected benefits of walkability (80).

Table 2.1 Characteristics of studies investigating associations between NBE features and CRF in youth (n=9)

Study	Design *	Population	NBE Variables and Measurements	CRF Measure ments**	Covariates	Statistical Methods
Vanhelst et al., 2013[19]	CS	N = 3,528 F = 52.27% Urban, European cities	Questionnaire: Heavy traffic, Secure bicycling, Walking routes, Outdoor fields, Gymnasiums near home	20-m shuttle run	Age, Sex, Fat mass, Fat-free mass, SES, Parental education, Pubertal status, Smoking	Backward stepwise linear regression
Oliveira et al., 2018[20]	CH	N = 583 F = 51.3% Urban, Portugal	Questionnaire: Residential density, Distance to facilities, Infrastructure (cycling, walking, maintenance), Safety (crime, traffic), Aesthetics, Pleasure	20-m shuttle run	Age, Sex, BMI, SES, Baseline fitness, BMI	Linear regression ANOVA
Putra et al., 2022(79)	CH	N = 1,874 F = 48.16% Urban-rural, Australia	Questionnaire: Perceived green space quality (parks, playgrounds)	PWC170	Sex, Caregiver education, Area disadvantage, Ethnicity, Family structure,	Multilevel Regression Models Two-Level Hierarchy **Clustering Effects**
Zewdie et al., 2021[21]	CS	N = 725 F = 43.86% Urban, USA (mostly Hispanic and Black)	Population-level data analysis: Child Opportunity Index (COI) Walkability, Greenspace, Access to healthy foods, Commute duration	PACER	Age, Sex, Area-level poverty, Race/Ethnicity	Generalized Linear Mixed Models (GLMMs) Hotspot Analysis Random Intercepts
James et al., 2020[22]	CS	N = 270 F = 38% Urban, UK	GIS, and data collected from Lle (geo-portal for Wales): Activity provision, Active travel routes, Public transport stops, roads, Green space	Cooper run	Sex, Home deprivation (WIMD), School deprivation (WIMD)	**Multivariate Linear Regression Structural Equation Modeling**

Cheah et al., 2012[18]	CS	N = 316 F = 51.6% Urban, Malaysia	Questionnaire: Neighbourhood Environment Walkability Scale for Youth (NEWS-Y): Residential density, Land use diversity, Street connectivity, Walking/Cycling infrastructure, Safety	20-m shuttle run	Sex, Parental education levels, Household income, Parental occupation	**Correlation Analysis**
Jilcott Pitts et al., 2013(80)	CS	N = 296 F = 55.7% Urban-rural, USA	Walk Score API, Street Smart Walk Scores: Amenity density, Crime data	YMCA	Grade, Sex, Race, Rural/Urban MVPA	**Bivariate Analyses:** Spearman correlation and linear regression.
Zewdie et al., 2023[17]	CH	N = 204,939 F = 48% Urban, USA (mostly Hispanic and Black)	Population-level data analysis: Child Opportunity Index (COI) Walkability, Greenspace, Access to healthy foods, Commute duration	PACER	Grade, Sex, Household poverty, Race/Ethnicity	Three-Level Generalized Linear Mixed Models
Noonan et al., 2016(78)	CS	N = 194 F = 55.2% Urban, UK	Questionnaire: Neighbourhood Environment Walkability Scale for Youth (NEWS-Y): Walkability, Recreation facilities, Land use mix, Street connectivity, Aesthetics	20-m shuttle run	Age, Sex, BMI z-score, Somatic maturation, Home environment	Analysis of covariance (ANCOVA) Multivariate analysis of covariance (MANCOVA) Linear regression analyses chi-squared tests

*Design: CS: Cross-sectional study; CH: Cohort study

**CRF Measurement Methods: *20-m shuttle run*: A progressive aerobic endurance test where participants run back and forth over 20 meters at increasing speeds; *PWC170*: Physical Work Capacity test at a heart rate of 170 beats per minute; *PACER*: Progressive Aerobic Cardiovascular Endurance Run, a multistage fitness test similar to the shuttle run, designed for younger populations; *Cooper run*: A 12-minute running test to measure the distance covered; *YMCA test*: A 3-minute step test where participants step up and down on a 30-cm bench at 24 steps per minute(higher heart rate indicates lower fitness)

Table 2.2 Summary of findings of studies investigating associations between NBE features and CRF in youth (n=9)

Study	NBE measures								
	Design			Diversity		Density	Desirability	Distance to public transport	Other/ Index or Scores
	Infrastructure/ walkability	Traffic	Greenspace	Active Facilities	Mixed Land use				
Vanhelst et al., 2013 *	Secure Bicycling and Walking Route	Heavy Traffic	Outdoor Fields	Gymnasiums near Home	Shop near Home				
Oliveira et al., 2018 **	Cycling and Walking Infrastructure, Network, Connectivity	Safety from Traffic		Distance to Local Facilities		Residential Density	Pleasure, Esthetics		
Putra et al., 2022 **			Perceived Quality of Greenspace						
Zewdie et al., 2021	Walkability		Greenspace		Access to Healthy Foods				Child Opportunity Index (COI)
James et al., 2020	Activity Provision, Active Travel Routes	Main Roads	Natural Resources	Activity Provider				Public Transport Stops	
Cheah et al., 2012	Street Connectivity Infrastructure for Walking and Cycling	Safety from Traffic		Access to Services	Land Use Diversity	Residential Density	Neighborhood Satisfaction		Walkability Scale: NEWS-Y
Jilcott Pitts et al., 2013 *									Walk Score
Zewdie et al., 2023 **	Walkability		Greenspace		Access to Healthy Foods				Child Opportunity Index (COI)
Noonan et al., 2016									High Deprivation

Green cells: Positive significant association
Orange cells: Negative significant association
Grey cells: Not significant association
*Indicates studies that accounted for MVPA as a covariate in the analysis
**Indicates cohort studies

2.3 Embracing Modern Analytical Methods for Exploratory Research

In recent years, there has been growing criticism regarding the extensive use of statistical testing, particularly in exploratory and descriptive research studies. These critiques recommend that exploratory research should move beyond focusing exclusively on statistical significance. Instead, researchers are encouraged to open the door to potential meaningful discoveries, embracing uncertainty and variability in data, and assessing the potential strength of an association by asking, "Is its effect meaningful enough to matter?" (81).

A new perspective advocates for shifting toward estimation and compatibility-based inference, emphasizing the magnitude and uncertainty of effects over binary p-value thresholds. Compatibility intervals, for instance, offer a nuanced view by presenting a range of plausible effect sizes, helping researchers evaluate the practical significance of findings. This approach aligns statistical methods more closely with the complexities of scientific inquiry, moving beyond the limitations of traditional significance testing. Historically, the dominance of p-value and statistical significance in scientific discourse has often led to oversimplified conclusions and a false sense of certainty. By adopting estimation-based methods that focus on effect sizes and confidence intervals, researchers can provide more comprehensive understanding of data. This transition represents a significant advancement, encouraging the exploration of relevance and practical implications rather than solely determining the presence or absence of effects (82).

To align with this paradigm shift, machine learning methods such as random forest offer a flexible and data-driven approach to exploring complex relationships. These methods prioritize prediction accuracy and interpretability, addressing practical questions such as "Which features are most important in predicting an outcome?" By moving beyond traditional statistical frameworks, machine learning bridges the gap between analytical rigour and real-world applicability, fostering deeper insights into multifaceted datasets.

2.3.1 Random forest

Random forest is an ensemble machine learning approach well suited for analyzing multidimensional datasets with numerous variables and interactions among predictors. Unlike traditional methods, random forest does not rely on assumptions about the linearity or the independence of variables. The application of random forest to research in NBE and health has grown due to its ability to handle the complexity inherent in such datasets. These studies often involve wide range of variables, including environmental features, socioeconomic factors, and individual-level covariates, which may interact in nonlinear ways (83). For instance, Yang et al. found that using random forest provided greater interpretability and revealed the nonlinear associations of the environment on walking (84). These advanced methods are expected to surpass traditional regression analyses and uncover more nuanced relationships between the built environment and health outcomes, enabling researchers to provide potentially more valuable insights and practical guidance for policymakers and urban planners (85).

2.4 Summary of the Literature Review

CRF is a vital marker of health, with higher levels linked to reduced cardiovascular risks and enhanced overall well-being across all populations, including youth. While CRF is well-known for its role in reducing cardiovascular risks and improving overall health, its levels among youth have declined significantly over recent decades. CRF appears to be shaped by a multifaceted combination of biological (e.g., genetics, age, sex), behavioural (e.g., physical activity levels, sedentary behaviour), and environmental (e.g., built environment, socioeconomic status) factors.

The built environment contributes substantially to the physical activity levels of young people, with favourable features such as accessible green spaces and walkable neighbourhoods often associated with higher levels of physical activity (74). Based on my exhaustive search, only nine studies investigated the relationship between the NBE and CRF in youth. These studies generally conclude that features such as walkability, green spaces, and proximity to recreational facilities are associated with higher CRF, while adverse factors such as heavy traffic are associated with lower CRF.

Limitations among the studies reviewed include the reliance on subjective measurements of the NBE, and inadequate consideration of confounders. While some studies accounted for covariates like age, sex, and socioeconomic status, few studies explored the role of physical activity which could be implicated in relation between NBE and CRF. Additionally, studies reviewed typically investigated limited set of features, and employed statistical methods that failed to capture the nonlinear relationships and intercorrelations among these variables. Furthermore, differences in physical growth, body composition, and physical activity behaviour between boys and girls may influence youth CRF and how the built environment relates to it, highlighting the value of sex-stratified analyses. However, only some of the studies explored gender differences in this area.

This review underscores the need for further research that addresses these limitations. There is a need to expand the range of NBE features analyzed, utilize more objective and comprehensive measures, and apply advanced analytical methods capable of capturing complex relationships. While there is a potential for informing intervention development, a greater understanding of the association between the NBE and CRF is needed; adopting rigorous methods to this end is warranted.

The following manuscript builds on the evidence gaps identified in the review, presenting detailed results that address the thesis'primary objective. To our knowledge, this is the first study that utilizes random forest modelling to examine associations between the NBE and CRF in youth. Given the novel application of this advanced statistical method, the manuscript is being prepared for submission to *Annals of Epidemiology*.

CHAPTER 3: MANUSCRIPT

What matters, and where? Features of the Neighbourhood Built Environment and Their Ability to Predict Cardiorespiratory Fitness in Youth: A Random Forest Approach

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3.1 Abstract

Background: Cardiorespiratory fitness is a critical indicator of youth health, and is associated with cardiometabolic outcomes and early-onset cardiovascular disease. Despite its importance, cardiorespiratory fitness levels among children and adolescents are declining globally. While the role of neighbourhood built environment in supporting physical activity is recognized, the contribution of neighbourhood built environment to cardiorespiratory fitness requires further investigation.

Purpose: To estimate the extent to which a range of neighbourhood built environment features may predict youth cardiorespiratory fitness.

Methods: Data were from the baseline visit of the Quebec Adipose and Lifestyle Investigation in Youth Cohort, an ongoing study comprising 630 children (aged 8-10 years at time of recruitment) who have at least one biological parent living with obesity. Analyses were restricted to participants living in the Greater Montreal Area (n=504). Cardiorespiratory fitness was assessed by measuring peak oxygen consumption (VO2peak) during a cycling test on an electromagnetic bike, adjusted for Fat-Free Mass (FFM) as measured by DXA. Moderate to vigorous physical activity was measured with accelerometry. Salient features of residential built environments were assessed using on-site audits and a Geographic Information System (GIS). Random forest was applied to assess the predictive capability of neighbourhood built environment features in relation to VO2peak/FFM, as a proxy for cardiorespiratory fitness.

Results: Among 504 children (mean age 9.6 ± 0.9 years; 54% boys), the mean VO2peak/FFM was (71.2 $min^{-1}{\cdot}kg\ FFM^{-1}$, SD = 13.8) among boys and (63.4 $min^{-1}{\cdot}kg\ FFM^{-1}$, SD = 11.4) among girls. The random forest model explained 33% of the variance in the outcome. The model identified BMI z-score, sex, and moderate to vigorous physical activity as the top three

predictors, followed by several neighbourhood built environment features, including density of streets with normal traffic, which favours walkability, number of intersections, vegetation index (NDVI), land use mix, building density and social disorder, indicated moderate predictive capability of neighbourhood built environment features.

Conclusions: This study identified several neighbourhood built environment features with a moderate to weak contribution in predicting cardiorespiratory fitness, beyond established sociodemographic factors and physical activity. These findings suggest that specific neighbourhood design features or transformations should be included in overall health promotion strategies, as these may contribute to enhancing cardiorespiratory fitness among youth, through increased physical activity and other mechanisms.

Keywords: Cardiorespiratory fitness, built environment, Neighbourhood, child

3.2 Introduction

Global declines in Cardiorespiratory Fitness (CRF) among youth have raised significant public health concerns (1,2). CRF, defined as the capacity of the circulatory and respiratory systems to deliver oxygen for energy production, is a strong predictor of cardiovascular disease and all-cause mortality in adults, and health outcomes in youth, including cardiometabolic health and early-onset cardiovascular disease. Moreover, CRF is associated with improved mental health by reducing the risks of depression and anxiety, boosting mood and self-esteem, and positively correlating with cognitive function and academic achievement (5–7).

Globally, CRF declined by approximately 7% from 1981 to 2014, with a more pronounced decline observed in boys compared to girls (2). A study conducted in Québec, Canada, also highlighted significant declines in CRF among youth over time, using the 20-m shuttle run test. Between ages 6 and 17 years, VO2max decreased by 14% in boys and 27% in girls (8). Social and built environmental changes, increasing obesity, sedentary behaviours, and reduced moderate to vigorous physical activity (MVPA) are likely all implicated in observed declines in CRF (9).

The built environment, comprises the physical spaces shaped or altered by humans that influence daily life (10). Urban design elements such as traffic, street connectivity, the availability of parks and green spaces, diversity, density, and desirability are associated with health outcomes (11). Notably, a large body of evidence supports the pivotal role of the built environment on child and adolescent physical activity (12).

Few studies have investigated the potential association between Neighbourhood Built Environment (NBE) and child and adolescent CRF, yielding mixed findings. For example, Vanhelst et al. reported that secure walking and bicycling routes, outdoor fields, and shops close to home were associated with higher CRF, while heavy traffic was linked to lower CRF (13). However, their study relied on adolescents' subjective responses to the Neighbourhood Environment Walkability Scale (NEWS), which may not accurately capture "true" environmental features. Adolescents who frequently use certain facilities, like parks or cycling routes, may be more likely to notice and report their availability, leading to information bias.

Similarly, Putra et al. reported no meaningful associations between perceived greenspace quality and CRF (14). Their study relied on caregivers' subjective reports to assess green space quality, which may reflect individual perceptions rather than actual characteristics of the environment. Interestingly, while higher walkability is generally associated with better CRF, Pitts et al. observed an inverse relationship between Walk Score and CRF, suggesting that factors such as traffic desirability and neighbourhood socioeconomic status may mitigate the benefits of walkability. The authors attributed these unexpected findings to a correlation between Walk Score and nearby crime rates (15). These findings underscore the multidimensional nature of the NBE and the importance of examining not only individual NBE features as independent determinants but also accounting for the broader context.

This study aims to estimate the extent to which a range of NBE features predict youth CRF by integrating detailed objective environmental assessments and utilizing the random forest model.

3.3 Methods

Study setting and participants

This study used data from the Quebec Adipose and Lifestyle InvesTigation in Youth (QUALITY) cohort, an ongoing investigation of the natural history of cardiometabolic health, along with the complementary QUALITY Residential Study. Six hundred thirty families with children aged 8-10 years at baseline were recruited from elementary schools across three cities in Quebec, Canada (Montreal, Quebec City, and Sherbrooke). Inclusion criteria included being of Western European origin, availability of both biological parents, and having at least one parent living with obesity (i.e., based on BMI computed from self-reported weight and height or on measured waist circumference). In the present study, we only used data collected during the initial (baseline) visit, and analyses were restricted to participants in the Greater Montreal Area (n = 504). Detailed procedures for the QUALITY study are described in Lambert et al. (16).

Covariates

Covariates were defined based on a Directed Acyclic Graph (DAG) (see supplementary material). The DAG was developed from the literature and refined through discussion and consensus among co-authors with expertise in built and social environments (T.B.), biostatistics and causal inference (T.S.), cardiometabolic risk factors (A.V.), CRF and physical activity (R.G.). Based on the developed DAG, the following covariates (potential predictors) were incorporated into the random forest model: age, sex, BMI z-score, Tanner stage, MVPA, neighbourhood poverty and prestige (indicators of SES), as well as NBE features, which are detailed below.

Measures

Body Composition

Anthropometric measurements were undertaken twice, and the average was retained. If there was a discrepancy greater than 0.2 cm for height and or waist circumference, or 0.2 kg for weight, a third measurement was performed, and the average of the two closest values was used. BMI z-scores were calculated according to the World Health Organization (WHO) guidelines (17). Participants were classified as normal weight (BMI z-score ≤1.0), with overweight (BMI z-score >1.0 and <2.0), or with obesity (BMI z-score ≥2.0) (18). Fat-free mass (FFM, in kg) was measured using dual-energy X-ray absorptiometry (DXA) (16).

Cardiorespiratory fitness

Among indicators of CRF, the peak oxygen (VO2peak) consumption measured during a maximal exercise test to exhaustion is widely considered a reliable and valid metric for assessing CRF in children and adolescents (12). In this study, VO2peak was measured during an incremental cycling test on an electromagnetic bicycle at maximal effort, which was indicated by either a heart rate of ≥195 beats per minute and/or a respiratory exchange ratio (VCO2/VO2) > 1.0 (16,19). VO2peak is influenced by various factors related to body composition, including sex, age, and maturity status (14). As recommended by Armstrong et al., we adjusted VO2peak for FFM (VO2peak ·min−1·kg FFM−1) (20).

Moderate to vigorous physical activity

To measure physical activity, we used data collected over 7 days from a uniaxial accelerometer (Actigraph LLC, Pensacola, FL, USA). Accelerometry data were downloaded as 1-min epochs and underwent standardized quality control and data reduction procedures (21). Data were considered valid if the accelerometer was worn for at least four days, including three weekdays plus one weekend day, with a minimum of 10 hours per wear day (22,23). Physical activity intensity was classified by thresholds: light (101–2295 counts per minute), moderate (2296–4011 counts per minute), and vigorous (≥4012 counts per minute) (18,24).

Neighbourhood built environment features

NBE characteristics were assessed through systematic social observation (audits) and MEGAPHONE, a geographic information system (GIS) that combines census and land-use data to characterize Montreal area neighbourhoods' social, built, and natural environmental features. Neighbourhood socioeconomic characteristics were derived from the 2006 Canadian Census data fusing population-weighted proportions and averages calculated for dissemination areas included in 500-metre network buffers centred on participants' residential locations (25). These measures included the percentage of households living below Statistics Canada's low-income cut-offs, single-parent families, unemployment rate, residents with a university degree, owner-occupied houses, recent movers (defined as those who had moved within the past year, as an indicator of residential stability), and average residential housing values. Principal components analysis identified two components: neighbourhood poverty and neighbourhood prestige (26).

Using the MEGAPHONE dataset, NBE indicators were computed for 1km street-network buffers around each participant's principal residence, including a vegetation index (NDVI), park area (proportion of buffer covered by parks), land use mix, density, number of intersections, density of streets with normal traffic (total length of streets in the 1km buffer with normal traffic during rush hour traffic), density of streets with heavy traffic (total length of streets in the 1km buffer with heavy vehicular traffic during rush hour) (27,28). Air quality data were from the Canadian Urban Environmental Health Research Consortium (CANUE), which provides annual estimates of fine particulate matter (PM2.5) averaged over a three year range (2005–2008 for the current study), to account for temporal variations (29). For most exposures, we used participants' 6 character postal codes, which typically identifies their precise street segment.

In addition to GIS-based measures, NBE characteristics were assessed using detailed on-site audits. In the spring of 2008, trained independent observers conducted detailed assessments of up to 10 street segments within the immediate residential neighbourhood. These assessments were performed using a validated checklist adapted from established neighbourhood assessment tools (30). Features assessed included presence of sidewalks, pedestrian aids (e.g., crosswalks, crossing lights/signs), traffic-calming measures (e.g., speed bumps, stop signs), and signs of social disorder (e.g., vandalism, litter, and abandoned structures). Inter-rater reliability was substantial for most items (kappa > 0.60) (31), and discrepancies were reviewed by a third observer or verified using

Google Street View (32,33). Details about the NBE variables measured in the study are provided in Table 3.1.

Table 3.1 Details of the NBE variables measured in the study

Variable	Definition	Source
Neighbourhood Poverty	A neighbourhood-level socioeconomic variable characterized by the percentage of households living below the low-income cut-off, dichotomized to low, average, high.	Census Data
Neighbourhood Prestige	A neighbourhood-level socioeconomic variable characterized by the percentage of residents with a university degree, dichotomized to low, average, and high.	Census Data
Traffic Calming Measures	The proportion of street segments with at least one traffic calming measures (speed bumps, mid-street segment stop signs, speed limit 30 km/h, traffic lights, large obstacles designed to decrease the number of driving lanes).	Audit
Pedestrian Aids	The proportion of street segments with at least one pedestrian aids (zebra crossing, pedestrian crossing light, pedestrian crossing sign, all-direction stop sign at intersection, widened sidewalk at intersection, paved pedestrian crossing, designated school corridor).	Audit

Social Disorder	Presence of graffiti, vandalism, litter, and abandoned building/construction.	Audit
Presence of Sidewalks	Presence of sidewalks (absent, present on one side only, present on both sides).	Audit
NDVI	Normalized Difference Vegetation Index (NDVI) based on satellite images of the amount of chlorophyll present, the index ranges from −1 to 1, with greater values indicating more vegetation.	GIS
Park Area	The proportion of the 1km buffer area covered by parks (<1%, 1%-5%, >5%).	GIS
Land use mix	A measure of land use mix (residential, commercial, industrial, recreational, or other) based on an entropy equation resulting in a score of 0 to 1 (34).	GIS
Building Density	Density of private dwellings per hectare (10,000 m2), dichotomized to high and low density.	
Heavy Vehicular Traffic	Density of streets within 1km buffers that have heavy vehicular traffic at rush hour (measured as the total length of streets [i.e., in km] and dichotomized as <1%, 1%-5%, or ≥5%).	GIS
Normal Vehicular Traffic	Density of streets within the 1km buffer that has normal vehicular traffic at rush hour (measured as the total street length [i.e., in km]).	GIS

Number of Intersections	Number of three-way -or more- intersections in 1km buffer.	GIS
Density of Highways	Density of highways in 1km buffer using Kernel Density Estimation.	GIS
PM2.5	Annual estimates of ground-level fine particulate matter (PM2.5).	GIS

Statistical analysis

Data cleaning and imputation

To address missing data issues, we applied Multivariate Imputation by Chained Equations (MICE) approach, as it is implemented in the 'mice' R package (version 3.16) (35). This iterative method uses regression models to generate multiple completed datasets, preserving data variability, reducing bias, and maintaining correlation structures between variables. The imputed datasets were expanded to a long format and included all five imputed datasets and the original dataset. Initially, MICE was applied to a dataset excluding NBE variables, which included all measurements related to peakVO2, MVPA, and sociodemographic variables. This step was performed to ensure that the outcome variable was not imputed based on the exposure variables. For the NBE variables, the proportion of missing data was very small (less than 3%), and therefore, a simple imputation was used, replacing missing values with the mean or mode based on the variable type. Finally, the two datasets were merged to create the full dataset for analysis.

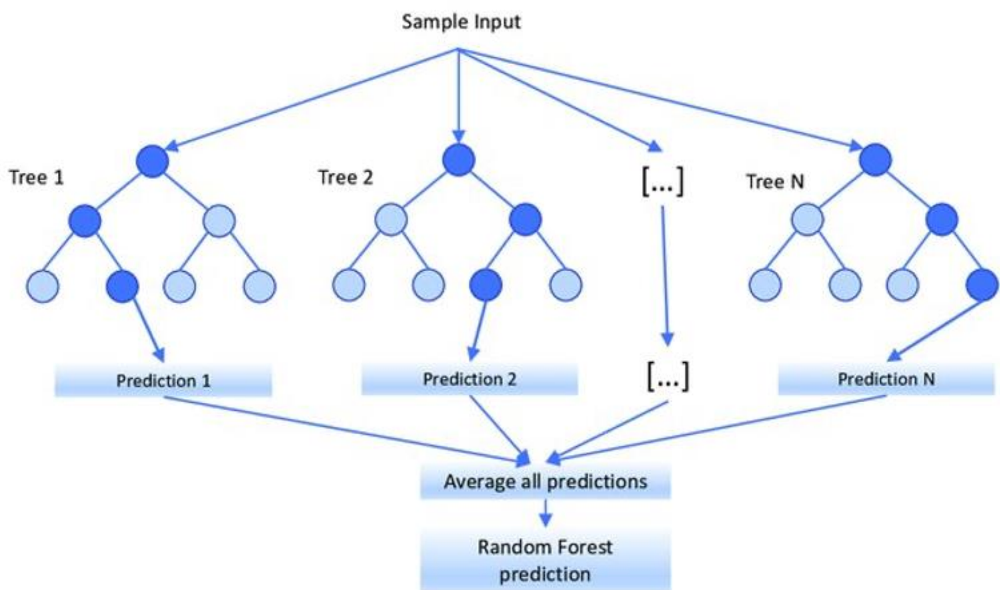
Data analysis

We used random forest, a supervised machine learning method, to assess the relative importance and predictive capabilities of predictor variables on VO2peak/FFM, the primary outcome variable of interest. Random forest is a powerful ensemble learning approach for building predictive and/or classification models based on variable inputs. Unlike traditional regression modelling, random forests do not require assumptions regarding the type of predictor-outcome relationship (e.g., linearity), nor do they assume independence (e.g., negligible multicollinearity) of the model covariates (36). Instead, they identify patterns based on the actual data, by minimizing cross-validated ('out-of-bag') prediction or classification error, making it a more flexible and accurate tool for capturing nonlinear dependence structures and intricate interactions across multiple predictor variables (37). These models can accommodate categorical and continuous variables, making them suitable for the mixed data types encountered in our study. Random forests, as an ensemble learning method, inherently combine hundreds of decision trees, each functioning as an individual prediction model (38).

This approach works by extracting multiple bootstrap samples from the original dataset and building a tree model for each. The data points that do not end up in each sample are called 'out-of-bag' samples and are used to assess the predictive performance of the respective tree model. This built-in cross-validation is a defining strength of random forests, especially when compared to traditional regression-based prediction models, which are prone to overestimating predictive accuracy.

The results of the multiple trees fitted within a random forest are ultimately aggregated, providing a robust assessment of the (average) predictive potential of the variable space. The importance of individual predictor variables is assessed by measuring the increase in prediction error, associated with removing one predictor variable at a time from the random forest model. Larger increases in prediction error indicate a stronger predictive capability of a single predictor variable. The increase in prediction error is typically quantified as 'relative increase in mean-squared error (%IncMSE)' and referred to as 'variable importance' (37). We constructed models using 1,000 regression trees, implemented via the random forest 4.7-1.2 R Package (39).

Figure 3.1 Random forest prediction scheme (40)



Based on the results of the random forest analysis we generated variable importance (VI) plots to identify the key predictors of VO2peak/FFM. The model's overall predictive performance was evaluated through the proportion of variability in VO2peak/FFM captured by the model (% variance explained), where higher percentages reflect greater predictive accuracy and effectiveness in accounting for the variability in the dependent variable (37). To further understand the contributing role of MVPA in predicting CRF, we removed MVPA from the model and compared the changes in variance explained and the relative importance of the remaining predictors to those in the initial model, which included MVPA.

To complement the random forest analysis and provide a more interpretable representation of the data, we constructed a single regression tree using the 'rpart' R package (41). The regression tree was generated using weighted imputed datasets to ensure that patterns reflected the integrated information from all imputations. Unlike the ensemble approach of random forests, which combines multiple trees to maximize predictive accuracy, a single regression tree serves as a simplified, hierarchical representation of the relationships between predictor variables and the outcome (VO2peak/FFM). Additionally, the regression tree highlights key decision thresholds and variable interactions, offering a visualization of how predictors are associated with the outcome.

3.4 Results

Among 504 children with a mean age of 9.6 (SD = 0.9) years, 230 were girls (46%). The mean household income was $43,200 and 54% of children had at least one parent with a university degree. The mean VO2peak/FFM was higher in boys (71.2 $min^{-1} \cdot kg\ FFM^{-1}$, SD = 13.8) compared to girls (63.4 $min^{-1} \cdot kg\ FFM^{-1}$, SD = 11.4), with the most compatible values for the difference ranging from 5.0 to 9.6 $min^{-1} \cdot kg\ FFM^{-1}$ (95% CI). Similarly, boys exhibited a higher mean of MVPA (59.6 min/day, SD = 28.2) compared to girls (43.4 min/day, SD = 19.9), with the most compatible values for the difference ranging from 11.0 to 19.4 min/day (95% CI). The mean VO2peak/FFM for the imputed dataset was lower (67.6 $\cdot min{-}1 \cdot kg\ FFM{-}1$, SD = 13.3) compared to the original data (69.2 $\cdot min{-}1 \cdot kg\ FFM{-}1$, SD = 12.8), with the most compatible values for the difference ranging from -0.2 to 3.4 $min^{-1} \cdot kg\ FFM^{-1}$ (95% CI). Detailed participant characteristics are presented in Table 3.2.

Table 3.2 Characteristics of study participants (n=504)

	Male (N=274)	Female (N=230)	Overall (N=504)
Mother BMI			
Mean (SD)	29.8 (6.8)	29.2 (6.3)	29.5 (6.6)
Median [Min, Max]	29.0 [18.7, 61.7]	28.9 [17.2, 51.1]	29.0 [17.2, 61.7]
Father BMI			
Mean (SD)	30.5 (5.5)	31.3 (6.0)	30.9 (5.7)
Median [Min, Max]	29.8 [18.6, 59.1]	30.4 [20.8, 59.1]	30.0 [18.6, 59.1]
Child Age			
Mean (SD)	9.6 (0.9)	9.6 (0.9)	9.6 (0.9)
Median [Min, Max]	9.6 [8.0, 11.1]	9.6 [8.0, 11.0]	9.61 [8.0, 11.1]
Tanner			
Initial(stage1)	248 (90.5%)	136 (59.1%)	384 (76.2%)
Stages >1	26 (9.5%)	94 (40.9%)	120 (23.8%)
BMI z-score categories			
Normal weight	158 (57.7%)	129 (56.1%)	287 (56.9%)
Overweight	77 (28.1%)	73 (31.7%)	150 (29.8%)
Obesity	39 (14.2%)	28 (12.2%)	67 (13.3%)

MVPA			
Mean (SD)	59.6 (28.2)	43.4 (19.9)	52.2 (26.0)
Median [Min, Max]	59.3 [6.7, 184]	39.1 [2.3, 116]	48.6 [2.3, 184]
VO2peak/FFM			
Mean (SD)	71.2 (13.8)	63.4 (11.4)	67.6 (13.3)
Median [Min, Max]	71.6 [35.3, 105]	64.3 [35.3, 103]	67.7 [35.3, 105]

The NBE features and socioeconomic characteristics were as follows: Mean total length of streets with normal within the 1 km street network buffer was 299 km (SD = 195), and the average number of intersections was 79 (SD = 39), indicating a well-developed road network (42). Density of streets with heavy traffic was relatively sparse, with 73% of observations falling into the category of less than 1% of streets with heavy traffic during rush hours, and only 8% in the category more than 5% of streets with heavy traffic during rush hours, suggesting relatively low levels of vehicular congestion. Land use mix scores had a mean of 0.4 (SD = 0.2), indicating moderate diversity in land use. The NDVI, averaged 0.3 (SD = 0.1), reflects vegetation density, with values ranging from -1 (minimal vegetation) to 1 (dense vegetation). Signs of social disorder, such as graffiti and litter, were absent in 66% of neighbourhoods but present in 34%. The average PM2.5 concentration was 9.8 µg/m³ (SD = 0.6), ranging from 6.6 to 11 µg/m³. (Table 3.3 includes further details regarding NBE measures available in supplementary).

Missing Data

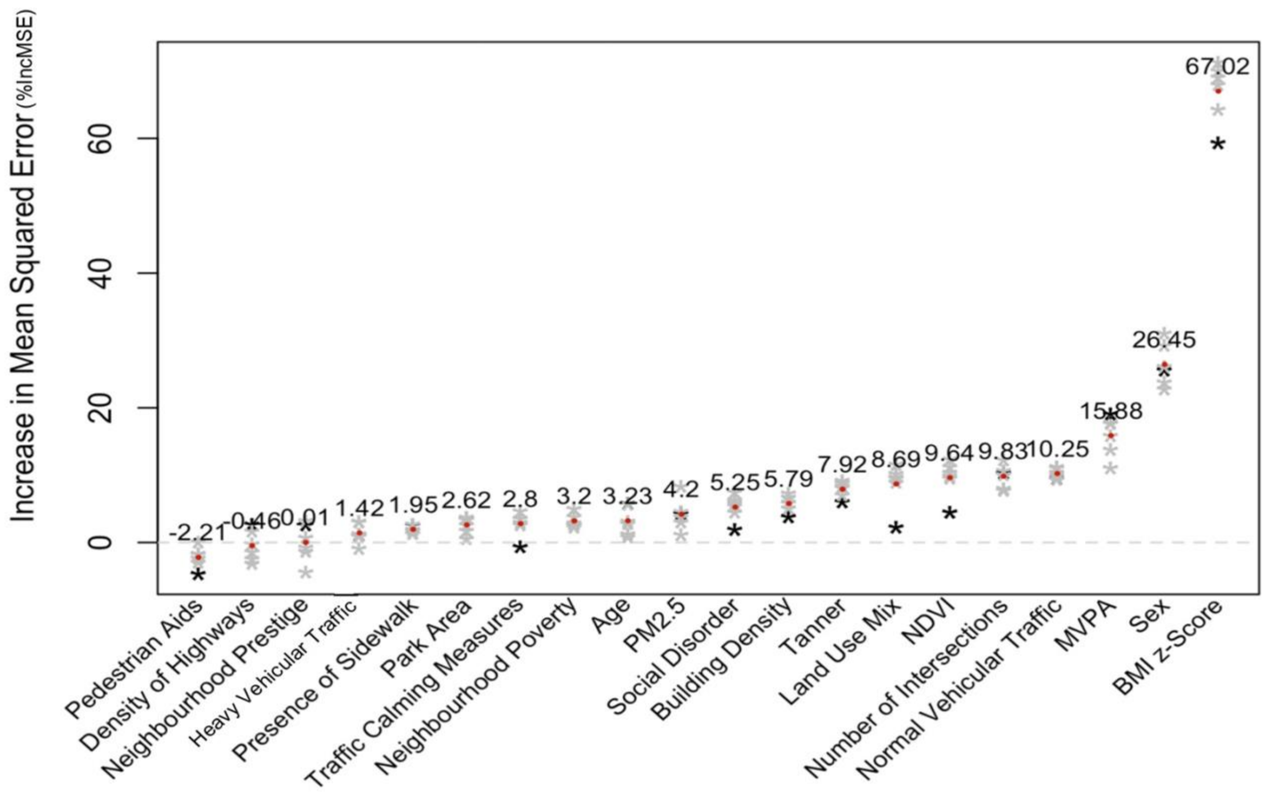
Approximately 30% of the VO2peak test data, adjusted for FFM, were missing, including data from invalid tests where maximum effort was not achieved. For the variables land use mix, PM2.5 and sidewalks, there were few missing data (1.5%, 1.5% and 2.5%, respectively).

Random forest analysis: predicting VO2peak/FFM

The primary random forest model, incorporating all covariates to predict VO2peak/FFM, used all imputed datasets (generated long-format data), explained 33% of the variance in the outcome. Figure 3.2 shows the relative importance of the predictor variables for each imputed dataset as well as for the original data set (complete case data with no imputation of missing data). The red dots represent the average increase in mean-squared error across all datasets. Based on the mean relative importance (%IncMSE) across all datasets, as indicated by the numbers in parentheses, the top three predictor variables were BMI z-score categories (*67*), sex (*26*), and MVPA (16). These were followed by NBE features including density of streets with normal traffic during rush hour (10), number of intersections (10), NDVI (9), and land use mix (9). The variables building density (6), social disorder (5), and PM2.5 (4) were identified as moderately important predictors of VO2peak/FFM, while neighbourhood poverty (3), traffic-calming measures (3), park area (3), sidewalks presence (2), and density of streets with heavy traffic during rush hour (1.4) had relatively lower importance scores. Variables with scores close to or below zero are deemed to be of negligible importance in predicting VO2peak/FFM.

For the top three variables, both the original and imputed data showed the same ranking; however, there was some uncertainty regarding other variables. For example, the relative importance scores of land use mix and NDVI were noticeably higher in the imputed datasets compared to the original dataset.

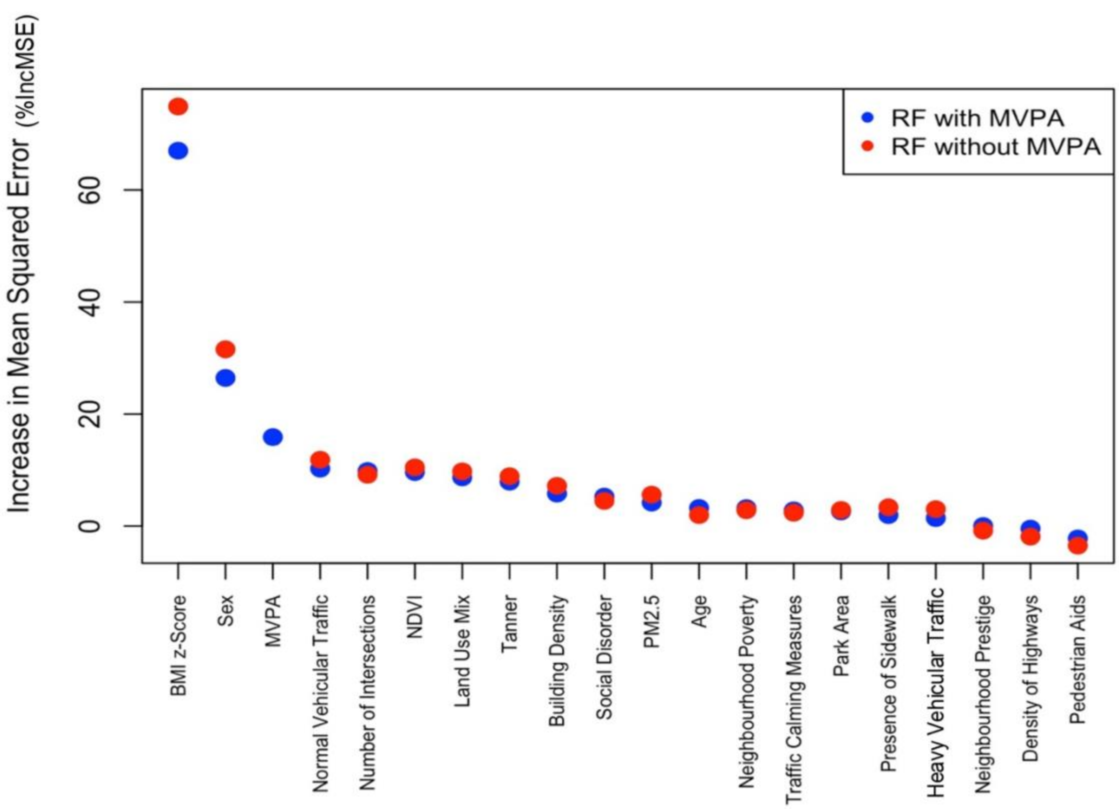
Figure 3.2 The relative importance of the predictor variables in predicting VO2peak/FFM based on the random forest mode



Grey dots represent the importance (%IncMSE) in the imputed datasets, black dots represent the importance (%IncMSE) in the original dataset, and the red dots represent the average importance (%IncMSE) across all datasets

Figure 3.3 displays the relative importance scores of predictors for VO2peak/FFM, estimated with two random forest models: one with and one without MVPA. In the absence of MVPA, the relative importance of predictors such as BMI z-score category, sex, density of streets with normal traffic during rush hour, and vegetation index relative importance(%IncMSE) increased, as the model placed greater emphasis on their roles in accounting for variability in the outcome. Excluding MVPA from the model marginally reduced the variance explained from 33% to 31.5%, suggesting that this reduction may be attributable to one or a combination of the following: (i) the relationship between NBE features and CRF likely engages mechanisms beyond the physical activity pathway, (ii) unmeasured factors may simultaneously influence both NBE and CRF, (iii) MVPA may serve as a near-perfect mediator of the effect of NBE on CRF.

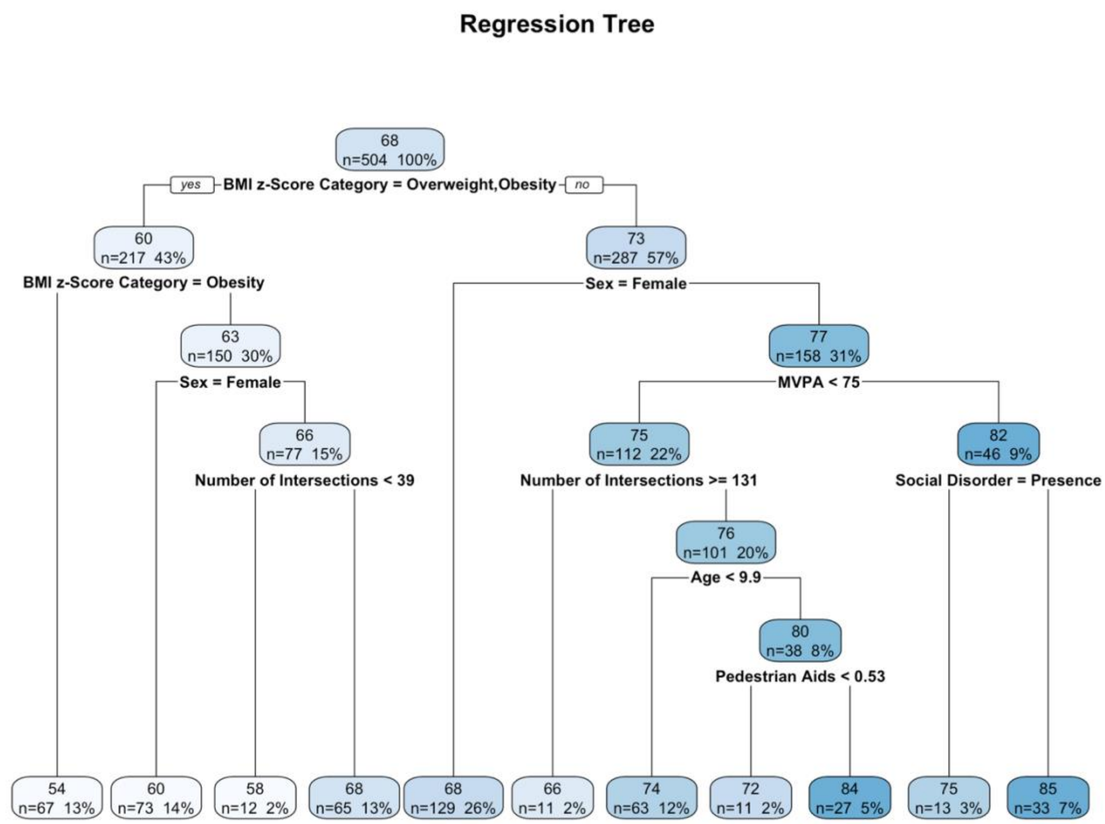
Figure 3.3 The relative importance of the predictor variables in predicting VO2peak/FFM, estimated by two random forest models, with and without MVPA



In Figure 3.4, the regression tree derived from the data shows each node's average VO2peak/FFM, illustrated by the top number in each box. The percentage indicates the proportion of the population with that particular profile, which, in some cases, was relatively small. There are multiple splits and many terminal nodes, characteristic of complex trees. It identifies the BMI z-score category as the most discriminating predictor of VO2peak/FFM, thus forming the initial split in the tree. Children categorized as having obesity exhibited the lowest VO2peak/FFM levels (54 VO2peak ·min−1·kg FFM−1), indicating poorer CRF. Among overweight children (BMI z-scores ≥ 1), sex further differentiated VO2peak/FFM, with distinct branches for males and females. For females in this group, the number of intersections within a 1 km buffer emerged as an important environmental factor, with fewer intersections (<39) correlating with reduced VO2peak/FFM levels (from 68 to 58 ·min−1·kg FFM−1).

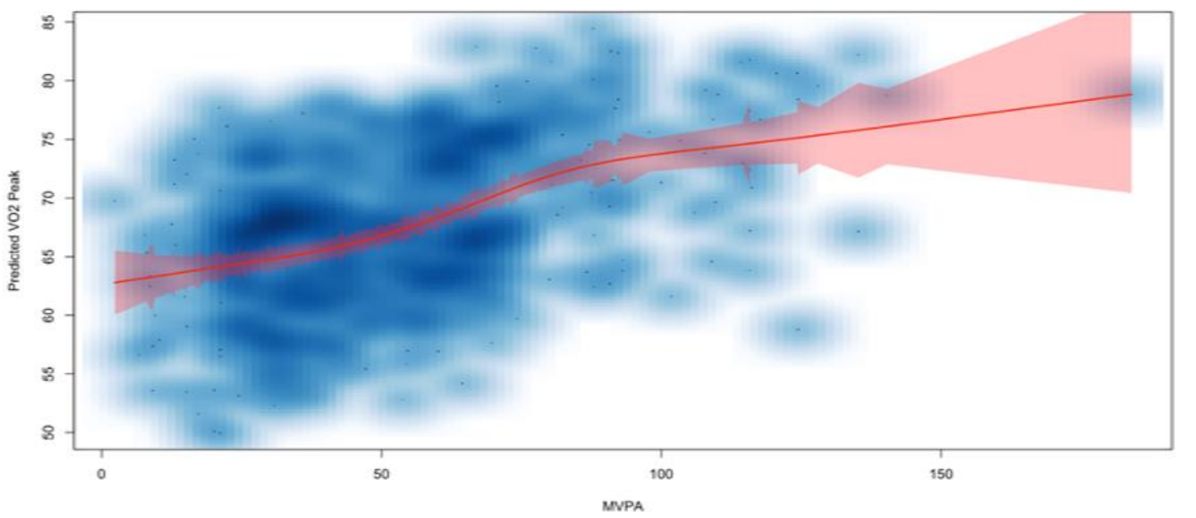
For children in the normal weight category, sex also played a significant role in differentiating higher vs lower VO2peak/FFM, with males further subdivided based on MVPA. Those with less than 75 minutes of daily MVPA exhibited lower VO2peak/FFM levels. In this group, a higher number of intersections (≥131) appeared to mitigate the decline in VO2peak/FFM (from 76 to 66 ·min−1·kg FFM−1). Additional splits highlighted the explanatory value of age (<9.9 years) and the availability of pedestrian aids being associated with reduced VO2peak/FFM. The presence of social disorder also emerged as an environmental factor in another branch (normal weight, boys, MVPA>75), where its presence was associated with lower VO2peak/FFM.

Figure 3.4 Regression tree based on the random forest model



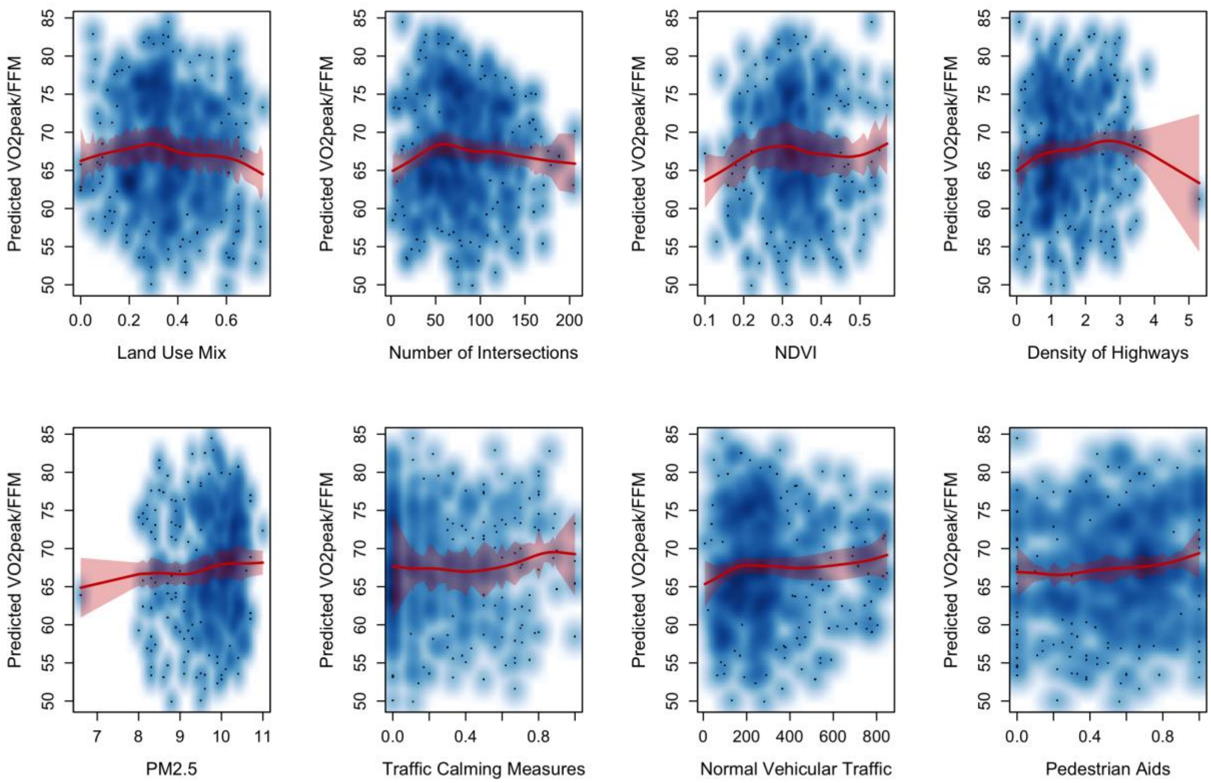
Figures 3.5 and 3.6 illustrate the bivariate associations between MVPA, NBE features, and predicted VO2peak/FFM, respectively, as determined by the random forest model. The density of the data is shown in blue shading, with darker regions indicating a higher concentration of data points. The red line indicates the fitted smooth splines, which represent the overall trend of the association, and the shaded red area around the line reflects the respective 95% confidence bands for the fitted trend line. As expected, higher MVPA was associated with higher predicted VO2peak/FFM.

Figure 3.5 Scatter plot showing the estimated association between MVPA and predicted VO2peak/FFM based on the random forest model



While the overall trend suggested that higher NDVI values were associated with slightly higher predicted VO2peak/FFM, the 95% confidence bands indicated variability in this relationship, particularly at the lower and upper extremes of NDVI. Similarly, the density of streets with normal traffic during rush hour showed a positive albeit weak trend with predicted VO2peak/FFM, with wide 95% confidence bands. For the number of intersections and land use mix, the trend initially increases but then declines, indicating the possibility of a nonlinear relationship.

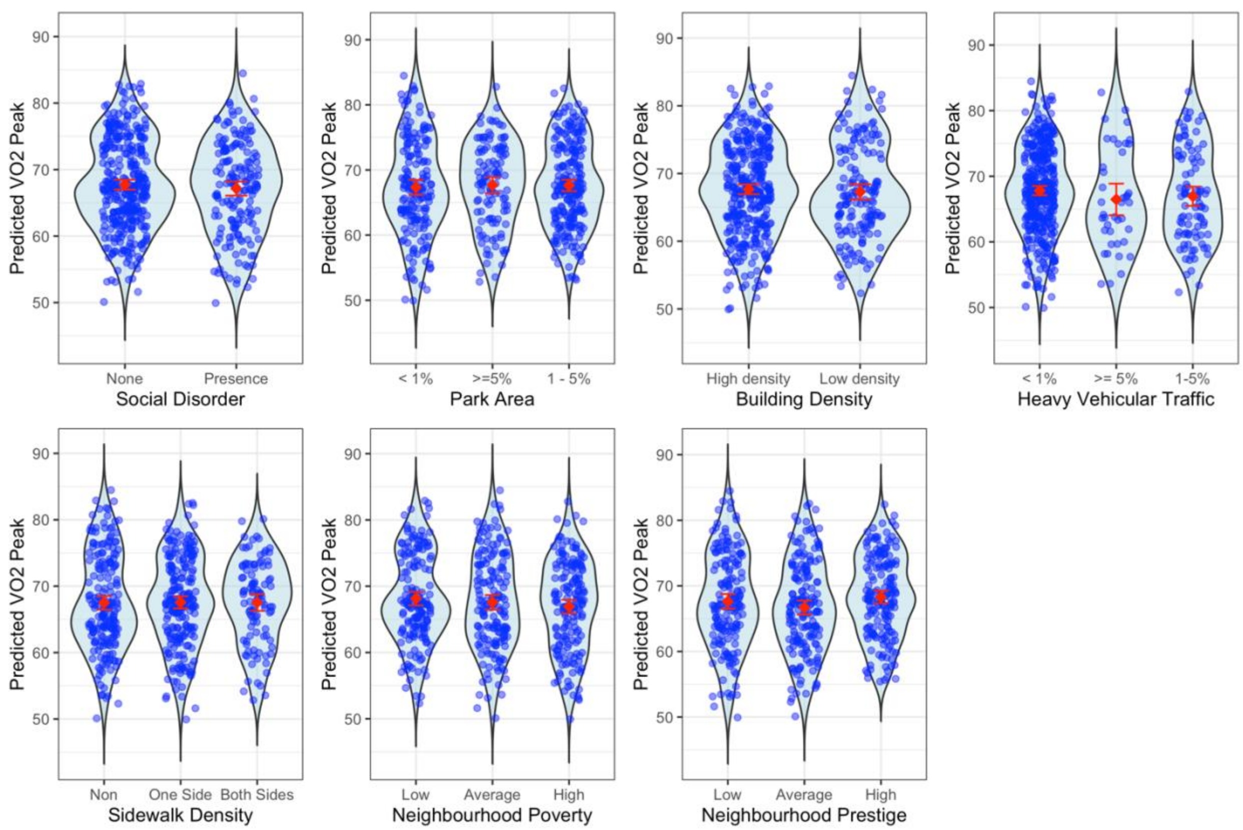
Figure 3.6 Scatter plots showing the estimated associations between NBE features and predicted VO2peak/FFM based on the random forest model



The association between VO2peak/FFM and categorical variables based on the random forest model is illustrated in Figure 3.7. The predictors are represented on the x-axis, while the y-axis shows the predicted VO2peak/FFM. The mean predicted VO2 peak (red dots) with associated red error bars offers a visual representation of variability within each group.

There are some differences in means in most variables; however, the range of values most compatible with our data and statistical model (95% confidence bands) encompassed a range of plausible associations. For example, children living in areas with greater social disorder tended to have slightly lower predicted VO2peak/FFM. Although the mean predicted VO2peak/FFM across different park area were almost identical, for park >=0.05, the concentration of points (blue dots representing individuals) tended to shift upward, suggesting a higher predicted VO2peak/FFM. Areas with sidewalks on both sides tended to have a marginally higher predicted VO2peak/FFM mean compared to areas with no sidewalks or partial sidewalks. Regarding neighbourhood socioeconomic status (indicated by neighbourhood poverty and neighbourhood prestige), the means suggested that individuals living in the high-prestige, low-poverty neighbourhood had a slightly higher predicted VO2peak/FFM.

Figure 3.7 Estimated associations between VO2peak/FFM and categorical variables, based on the random forest model



3.5 Discussion

In this study, we aimed to estimate the association between NBE features and CRF in youth. The mean VO2peak/FFM observed in our cohort was 67.6 ·min−1·kg FFM−1 (SD = 13.3), which is relatively higher than the mean reported in other studies (43,44). Given the limited number of studies reporting CRF adjusted for fat-free mass, direct comparisons are limited, and the observed difference may be attributed to the sociodemographic characteristics of our sample. The random forest model incorporating demographic characteristics, BMI z-score, sex, age, Tanner stage, socioeconomic indicators (neighbourhood poverty and prestige), as well as multiple NBE features, explained 33% of the variance in CRF. This level of explained variance is acceptable for multifactorial models in health research, capturing a reasonable portion of variability while acknowledging the influence presence of unmeasured factors (45). Based on the random forest model, BMI z-score, sex, and MVPA were the most important predictors of CRF, consistent with findings from previous studies (4). We also identified several salient NBE features, including density of streets with normal traffic during rush hour, number of intersections, land use mix, greenspace (NDVI), building density, and social disorder, as additional important predictors (24).

Our results suggest that number of intersections and the density of streets with normal traffic are key indicators of the built environment that can influence CRF by promoting physical activity. Higher intersection density improves walkability by providing more route options and shorter travel distances, which encourages active transportation like walking and cycling (46). The density of streets with normal traffic volumes is linked to reduced traffic-related safety concerns, fostering a safer and more supportive environment for physical activity (47). Consequently, these environmental features support the development and maintenance of CRF, consistent with findings by Vanhelst et al. (13). Similarly, Zewdie et al. reported positive associations between walkability, green space, and CRF among youth (48). Our study extends these findings by incorporating objective measures of the built environment and exploring additional aspects such as diversity (measured through land use mix), density (captured by population and building density), and desirability (assessed through indicators such as signs of social disorder).

The findings suggest that some NBE features may be associated with CRF in a nonlinear way. For instance, the regression tree showed that having fewer than 39 or more than 139 intersections within a 1 km buffer was associated with lower CRF levels. A possible explanation for this trend could be that a very low number of intersections are indicative of sparse or poorly connected neighborhoods, limiting opportunities for active transportation such as walking, rolling or cycling. Conversely, a very high number of intersections might signify densely populated urban areas with increased traffic congestion, reduced safety, and lower air quality, which could discourage physical activity and negatively impact CRF. Similarly, scatter plots illustrated a trend whereby CRF initially increased with the number of intersections and land use mix but then declined beyond certain thresholds. These findings align with prior studies pointing to nonlinear relationships between NBE and physical activity (49,50). This highlights the strength of random forest modelling in identifying nonlinear patterns that traditional methods might overlook.

Methodological Considerations

In recent years, there has been a surge in criticism of the prevalent overuse of statistical testing, particularly in exploratory and descriptive research studies (51). Critics underscore the pressing need for a paradigm shift in research focus beyond the sole emphasis on statistical significance (52). They propose instead a greater acceptance of uncertainty and variation and a more meaningful assessment of the potential strength of a given association, asking, "Is its effect meaningful enough to matter?" (52). Given the multidimensional nature of the built environment dataset, applying a supervised machine learning approach, to wit, random forest, to estimate the relative importance and predictive capabilities of NBE features on youth CRF, largely satisfies these recommendations.

Strengths and Limitations

We applied the Multivariate Imputation by Chained Equations (MICE) method to address potential bias from non-random missingness. This method preserves data variability and variable relationships. Generating multiple imputed datasets provided a comprehensive assessment while accounting for uncertainty due to missing values. Additionally, we employed rigorous and validated methods to optimize measurement accuracy, in particular by using VO2peak, adjusted for fat-free mass, as an indicator of CRF. In addition, the integration of GIS data, on-site audits, and air quality metrics offered a multifaceted assessment of the built environment, enhancing the depth and scope of our findings.

The cross-sectional design limits inferences on causality and the ability to capture changes or dynamic processes over time. However, findings could serve as a valuable starting point to identify associations and generate hypotheses for future longitudinal studies. The sample is predominantly from high socioeconomic backgrounds, urban and suburban areas, and families with higher rates of overweight or obesity, which may limit the generalizability of the findings. Additionally, the study did not account for neighbourhood self-selection, wherein individuals may choose environments aligned with their lifestyle preferences. However, as the participants herein were aged 8–10 years, the likelihood of direct self-selection by children is minimal. While parental choices may still reflect certain lifestyle preferences, the potential influence of self-selection is likely to be less prominent in this context.

While random forest modelling provides valuable insights, there are inherent limitations. As a "black-box" method, interpretability may be limited (53). Additionally, random forest identifies associations but cannot definitively establish causality. The sample size may have limited predictive power in this study, and overfitting to noise remains a potential concern despite efforts to tune the model (53). Future studies could address these limitations by increasing sample sizes to reduce overfitting, and refining hyperparameters such as the number and depth of trees to improve model performance.

3.6 Conclusion

Our study is among the first to apply random forest modelling to estimate associations between the NBE and CRF in youth. The findings highlight the potential influence of NBE features on youth CRF, offering a more nuanced perspective through machine learning techniques. These findings offer valuable insights that warrant further exploration. The evidence could be useful for urban planners, public health officials, and other interest holders dedicated to fostering healthy, active lifestyles in young populations.

3.7 Acknowledgement

Dr. Marie Lambert (July 1952 – February 2012), pediatric geneticist and researcher, initiated the QUALITY cohort. The QUALITY study was funded by the Canadian Institutes of Health Research (CIHR), the Heart and Stroke Foundation of Canada (HSFC), and the Fonds de la Recherche du Québec en santé (FRQS). The complementary studies on the QUALITY Residential and School Built Environment were also supported by the HSFC and CIHR. PM2.5 metrics, indexed to DMTI Spatial Inc. postal codes, were provided by CANUE (Canadian Urban Environmental Health Research Consortium).

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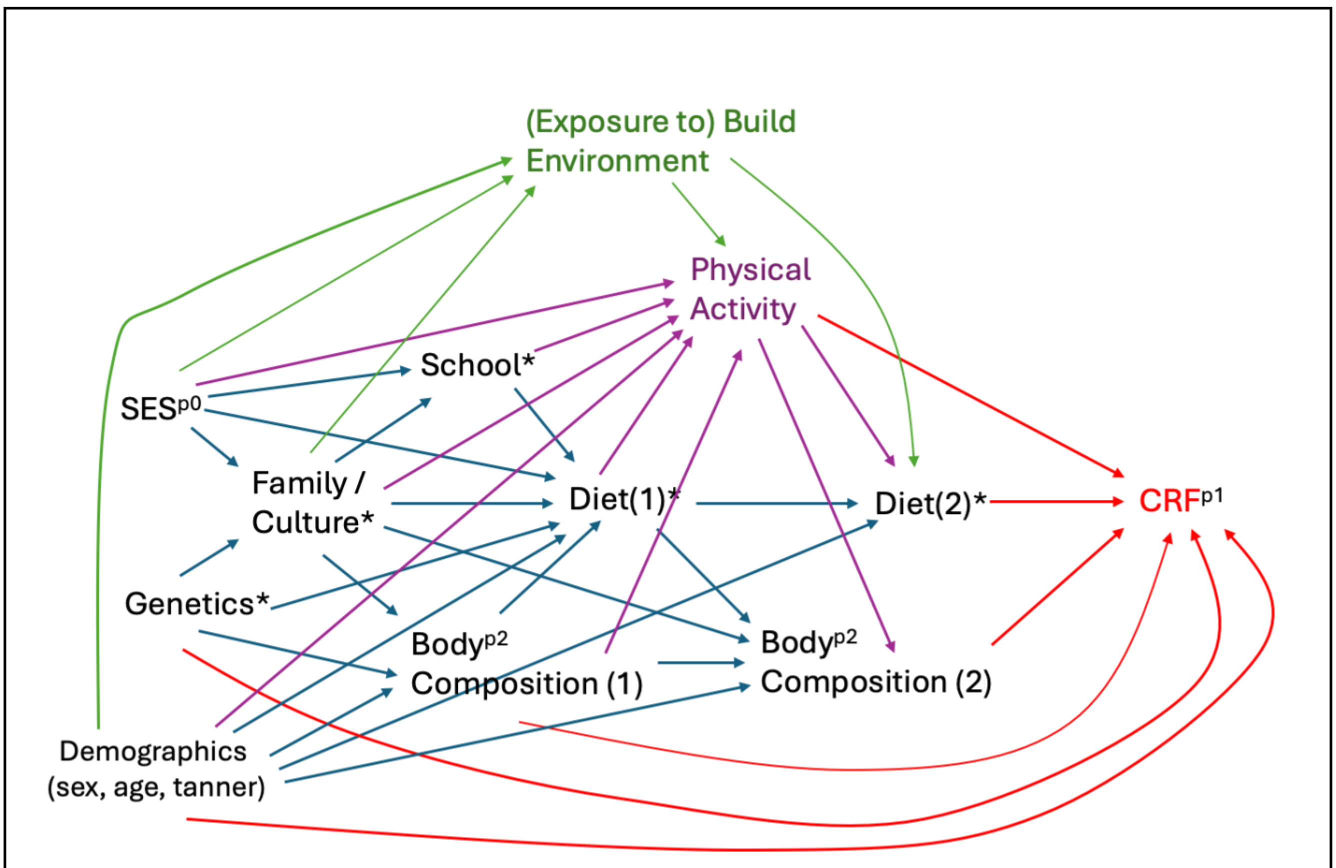
3.9 Supplementary

Figure 3.8 Directed Acyclic Graph of presumed causal relationships between neighbourhood built environment features, CRF and various covariates



*not measured / no proxy measure available in this study

p0 proxy measure available: neighbourhood level data on house income

p1 proxy measure available: PeakVO2/FFM

p2 proxy measure available: BMI z-score

Diet 1 and Diet 2, as well as Body Composition 1 and Body Composition 2, represent sequential time points.

Table 3.3 Characteristics of NBE measures and socioeconomic indicators

Measure	**Overall (N=504)**	**Measure**	**Overall (N=504)**
PM2.5		**Normal Vehicular Traffic**	
Mean (SD)	9.8 (0.6)	Mean (SD)	299 (195)
Median [Min, Max]	9.9 [6.6, 11]	Median [Min, Max]	254 [7.5, 849]
Number of Intersections		**Heavy Vehicular Traffic**	
Mean (SD)	79 (39)	< 1%	369 (73%)
Median [Min, Max]	76 [2 , 206]	>= 5%	41 (8%)
		1-5%	94 (19%)
Land Use Mix		**Presence of Sidewalks**	
Mean (SD)	0.4 (0.15)	No Sidewalks	193 (38%)
Median [Min, Max]	0.35 [0, 0.7]	Partial Sidewalks	211 (42%)
		Sidewalks Both Sides	100 (20%)
NDVI		**Traffic Calming Measures**	
Mean (SD)	0.33 (0.08)	Mean (SD)	0.25 (0.25)
Median [Min, Max]	0.32 [0.10, 0.57]	Median [Min, Max]	0.20 [0, 1]
Social Disorder		**Park Area**	
None	334 (66 %)	< 1%	171 (34%)

Presence	170 (34 %)	>= 5%	111 (22%)
		1- 5 %	222 (44%)
Neighbourhood Poverty		**Building Density**	
Low	168 (33%)	High Density	346 (69%)
Average	166 (33%)	Low Density	158 (31%)
High	170 (34%)		
Neighbourhood Prestige			
Low	165 (33%)		
Average	169 (33%)		
High	170 (34%)		

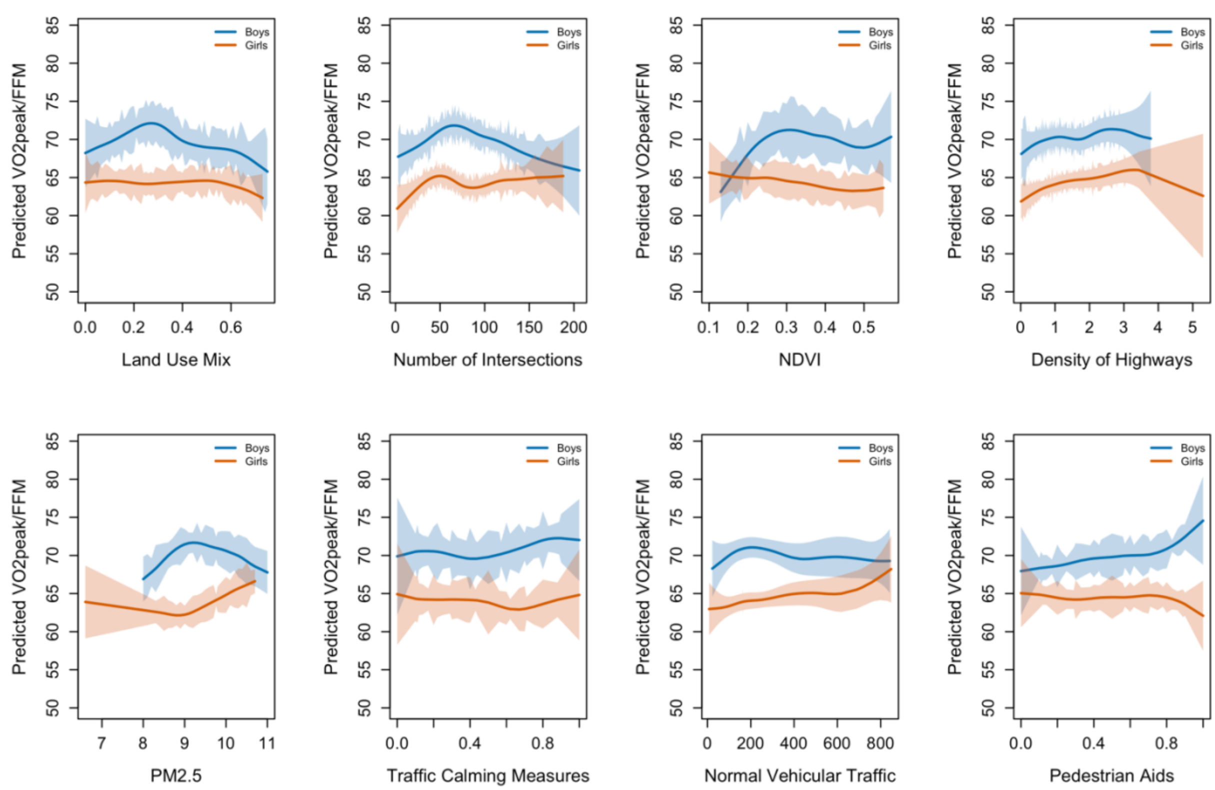
Following Chapter 3, Chapter 4 provides supplementary analyses that extend the findings to address the supplementary objective, which was excluded from the manuscript due to journal space limitations. These analyses explored the associations between the Neighbourhood Built Environment (NBE) and Cardiorespiratory Fitness (CRF) in youth, incorporating stratified data and detailed visualizations. Chapter 4 aims to enhance the understanding of gender-specific patterns and nuanced trends observed in the main study.

CHAPTER 4: ADDITIONAL ANALYSES and RESULTS

To examine whether the associations between NBE features and predicted VO2peak/FFM differ by gender, stratified data analyses were performed using the same analytical approach described in the manuscript. Subsequently, the associations between predictors and predicted VO2peak/FFM were visualized using scatter and violin plots.

The results revealed distinct gender-specific patterns in the relationship between environmental predictors and predicted VO2peak/FFM, with boys generally exhibiting higher CRF levels than girls. A modest positive relationship between the NDVI and predicted VO2peak/FFM was observed among boys. In contrast, the trend remained flat among girls, with wide 95% confidence bands indicating high variability. The number of intersections suggested a nonlinear trend in both groups, peaking at around 50 for girls and 60 for boys before declining, with more pronounced changes among boys. For land use mix, a positive association at lower values was observed among boys, peaking at around 0.3, followed by a slight decline at higher levels. In contrast, no meaningful associations were discerned among girls. Other predictors, such as pedestrian aids and traffic-calming measures, exhibited limited or no clear associations with predicted VO2peak/FFM for both boys and girls, with wide 95% confidence bands.

Figure 4.1 Scatter plots illustrating the estimated associations between continuous NBE features and predicted VO2peak/FFM, stratified by gender, based on the random forest model



Among boys, residing in neighbourhoods with signs of social disorder (Vs no disorder) was associated with lower predicted VO2peak/FFM. No association between disorder and CRF was observed among girls. Girls exhibited slightly higher mean VO2peak/FFM in areas with lower (Vs higher) density of heavy traffic. However, the values most compatible with our data and statistical model (95% confidence bands) spanned a range that included the possibility of no meaningful difference across traffic categories. The mean VO2peak/FFM for boys remained relatively consistent across traffic levels. Residential building density and park area ratio showed no substantial differences across categories for either boys or girls, with 95% confidence bands covering a range of plausible values.

Figure 4.2 Violin plots illustrating the distribution of predicted VO2peak/FFM across different categories of NBE features among girls, based on the random forest model

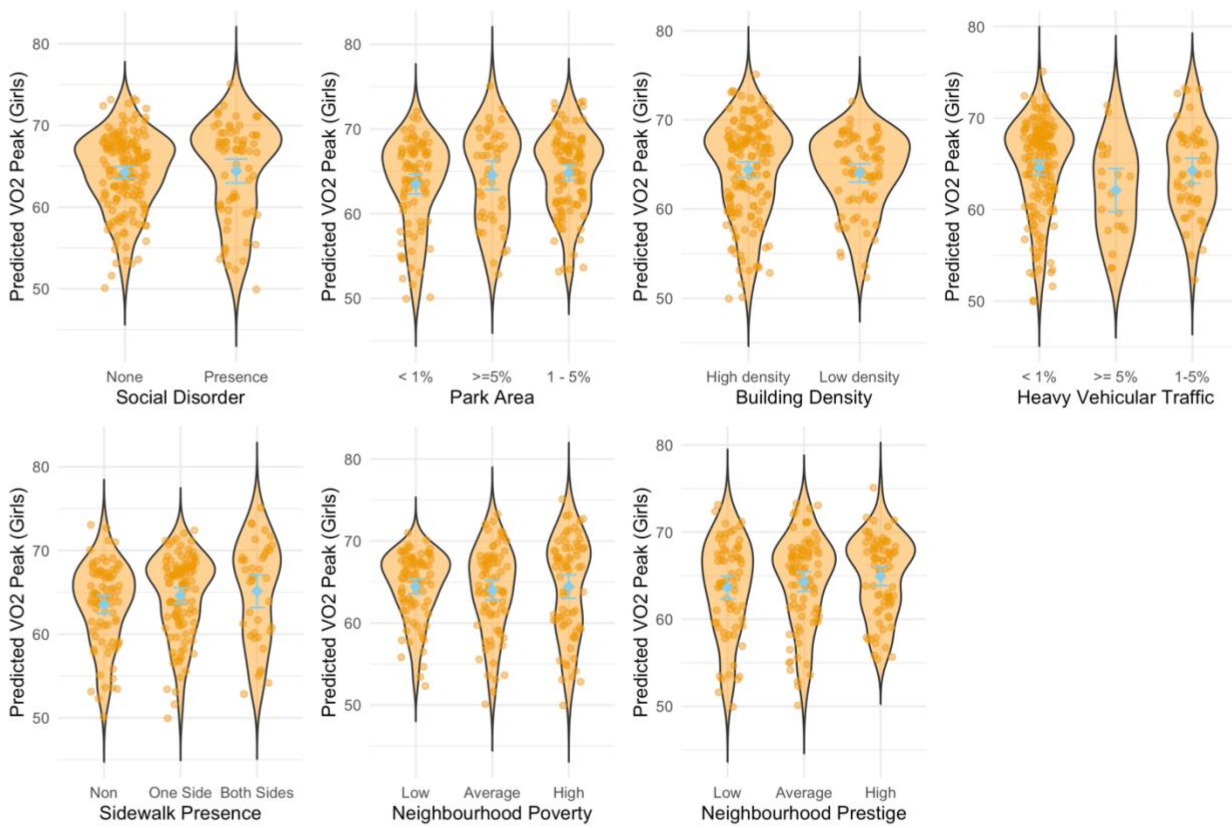
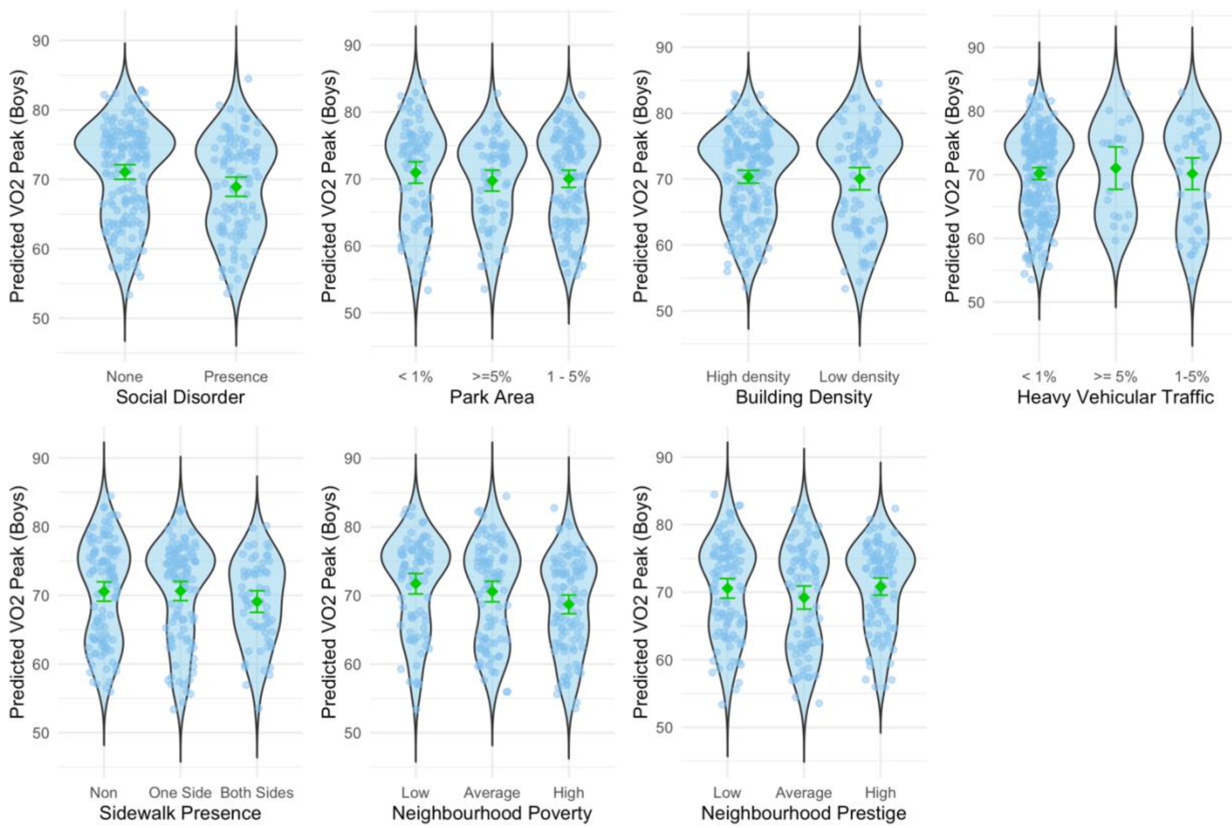


Figure 4.3 Violin plots illustrating the distribution of predicted VO2peak/FFM across different categories of NBE features among boys, based on the random forest model



Following Chapter 4, Chapter 5 provides a discussion of the findings, highlighting their significance, strengths, and limitations. It explores the broader relevance of these findings to family medicine and underscores opportunities for future research and practical applications. The chapter concludes by summarizing the key contributions of this thesis.

CHAPTER 5: DISCUSSION and CONCLUSION

5.1 Summary of Findings

The primary objective of this thesis was to estimate the extent to which various Neighbourhood Built Environment (NBE) features predict youth Cardiorespiratory Fitness (CRF). Additionally, this study aimed to examine the relationships between NBE and predicted CRF separately for boys and girls using stratified data.

The primary objective was extensively addressed in the enclosed manuscript. Findings from the random forest model demonstrate that, beyond established predictors such as BMI, sex, and MVPA, NBE features, including density of streets with normal traffic, number of intersections, NDVI (vegetation index), and land use mix, also contribute to predicting CRF. A comparison of models with and without MVPA showed a slight decrease in the explained variance, from 33% to 31.5%. This reduction may be due to one or a combination of the following: (i) the relationship between NBE features and CRF likely engages mechanisms beyond the physical activity pathway, (ii) unmeasured factors may simultaneously influence both NBE and CRF, (iii) MVPA may serve as a near-perfect mediator of the effect of NBE on CRF. Nevertheless, further analysis is needed to explore the exact role of MVPA in this association.

Scatter plots illustrating the relationship between continuous NBE features and predicted CRF, based on the random forest model, showed weak positive associations between NDVI and the density of streets with normal traffic and CRF. However, the confidence bands (shaded red area) indicated variability and uncertainty in these relationships. Nonlinear patterns were observed for variables like land use mix and the number of intersections.

For categorical variables, violin plots revealed minor differences in mean CRF across groups; however, the range of values most compatible with our data and statistical model included a range of plausible associations (95% confidence band). For instance, areas with no signs of social disorder and higher park area (≥5%), as well as neighbourhoods with high prestige and low poverty, showed slightly higher mean predicted CRF.

The stratified analysis by sex suggested potential gendered patterns, with stronger estimated associations between NBE predictors and predicted CRF in boys than in girls. A modest positive association was observed between NDVI and predicted CRF, along with nonlinear trends between the number of intersections, land use mix, and predicted CRF among boys. In contrast, these predictors showed minimal or negligible associations among girls, with flat trends and wide 95% confidence bands.

The overall trends observed in the full sample aligned more closely with those observed among boys. Trends among girls were generally weaker or flatter, indicating that boys may be driving the overall associations in the combined analysis. The associations for predictors such as NDVI and signs of social disorder also seemed to be stronger among boys than girls, apparently diluting overall trends when data for both sexes were combined. Thus, stratified data highlight sex-specific nuances that were obscured in the combined data, reinforcing the importance of conducting separate analyses to effectively capture these differences. These findings provide additional evidence that responses to environmental cues and prompts differ between boys and girls.

These findings are consistent with previous studies showing sex-specific differences in the association between NBE and fitness. For example, Zwedi et al. and Oliveira et al. reported that associations between some NBE predictors and fitness were more apparent in boys than in girls (21,20). Other studies examining other components of fitness have also reported some gender-specific patterns. For instance, Smith et al. observed that pedestrian connectivity was positively associated with fat-free mass (FFM) in boys, but not in girls, while Hsieh et al. reported that park space was linked to lower body fat percentage in girls but not boys (86,87).

5.1.1 Strengths

In this study, we integrated GIS data, on-site audits, and air quality metrics to provide a multidimensional perspective on the relationship between NBE and adolescents' CRF. The missing data related to VO2peak/FFM primarily resulted from invalid tests, where participants did not reach maximum effort during the cycling test. This issue was more common among children with lower CRF levels. While this non-random missingness could have introduced bias, the use of the Multivariate Imputation by Chained Equations (MICE) approach effectively addressed this issue. By preserving the relationships between variables, this method minimized potential biases and supported the reliability and robustness of the findings (88).

Advanced machine learning techniques, such as random forest, enabled the identification of nonlinear relationships and the relative importance of NBE features, addressing the limitations of traditional statistical methods. Stratified analyses offered preliminary insights into gender-specific patterns, which might inform future research and targeted interventions. While the exploratory nature of the analyses limits the ability to draw definitive conclusions, the approach and findings provide valuable insights for interest holders. Moreover, this study highlights the potential of advanced methods like random forest for identifying complex, nonlinear relationships and key predictors in exploratory research. By doing so, it offers a practical framework for researchers exploring the multidimensional associations of the built environment on health outcomes.

5.1.2 Limitations

While this study offers valuable insights into the association between neighbourhood environments and adolescent fitness, its limitations should be acknowledged to interpret findings with an appropriate level of caution. The cross-sectional design prevents establishing causality and capturing dynamic changes over time. The sample, primarily from urban, high socioeconomic families with higher rates of overweight or obesity, limits the generalizability of findings to more diverse populations. Neighbourhood self-selection may also confound associations, as families often choose environments aligned with their lifestyle preferences.

Additionally, this study only examined the immediate neighbourhood around participants' homes, whereas other environments, such as school neighbourhoods, may also be associated with children's fitness. However, given that children aged 8–10 years typically spend the majority of their time within their residential neighbourhoods, features within residential built environments remain particularly salient. While random forest modelling provides valuable insights, its data-driven nature introduces limitations. The method relies heavily on the quality and quantity of input data, which can amplify issues in small or unbalanced datasets, potentially skewing results. Additionally, random forest models are prone to overfitting, particularly with small sample sizes or noisy data, which could limit the validity of the interpretations.

5.1.3 Recommendations for Future Research

Longitudinal studies are needed to examine how changes in neighbourhood features influence CRF over time and to provide a stronger basis for causal inferences. Increasing sample sizes, tuning hyperparameters, and integrating complementary methods could enhance model robustness and interpretability. To enhance generalizability, future research should include diverse populations across broader age groups, socioeconomic statuses, and cultural contexts, addressing potential disparities. Self-selection biases could be accounted for using validated questionnaires and integrating responses into analyses in order to differentiate environmental effects from pre-existing preferences.

Future studies could offer a more nuanced understanding of the complex interplay between the NBE, MVPA, and CRF by employing VanderWeele's four-way decomposition method. This approach quantifies the proportion of the effect attributed to being direct (independent of mediation or interaction), interaction only, mediation only, or a mediated interaction (89). Future studies could also explore additional covariates, such as participation in extracurricular sports, access to social support networks, and parental involvement. as potential mediators or moderators in the relationship between NBE and CRF. Lastly, the interaction between social and built environment factors warrants further investigation, with studies assessing these dimensions together to better understand their combined impact on adolescents' fitness outcomes.

5.2 Significance to the Field of Family Medicine

Family medicine emphasizes patient-centred care, adopting a holistic approach that considers the complex interplay of health determinants within the community context. My thesis contributes to this perspective by providing family physicians with evidence-based insights into how NBE influence youth cardiorespiratory fitness. While family physicians are not expected to master urban planning, understanding these environmental determinants can enrich their ability to offer comprehensive and contextually relevant care.

Family medicine adopts a patient-centred, holistic approach, addressing the complex interplay of health determinants within the community. My thesis contributes to this framework by providing evidence-based insights into how NBE could influence youth cardiorespiratory fitness. While family physicians are not expected to master urban planning, this knowledge equips them with a deeper understanding of environmental determinants that shape health outcomes, enabling them to deliver more comprehensive and contextually relevant care.

Aligning with the CFPC's principles, this research supports family physicians as skilled clinicians by integrating interdisciplinary knowledge from public health, urban planning, and environmental science into their practice (90). Understanding the influence of neighbourhood environments allows family physicians to better address the link between individual health and the places where patients live and play. Additionally, these insights empower family physicians to advocate for community-level interventions and policies that foster favourable environments. By doing so, they promote preventive care and help mitigate the burden of chronic diseases within their patient populations.

Beyond individual care, this research emphasizes family medicine's role as a community-based discipline. These findings align with the vision of the 2019 Patient's Medical Home (PMH) model, which highlights the importance of community engagement and addressing social determinants of health (91). By advocating for healthier neighbourhood designs and resources, family physicians can extend their impact beyond the clinic, contributing to the creation of supportive environments that enhance both individual and community well-being.

5.2.1 Expanding Knowledge Translation

The use of advanced methodologies, such as random forest modelling, introduces innovative tools to Family Medicine research. These methods are particularly useful in analyzing multidimensional data and understanding how various factors interact to influence health. These techniques enhance the quality of insights and have the potential to transform healthcare research, especially in areas with multifactorial outcomes. They provide a solid foundation for developing targeted interventions, such as modifying built environments to promote youth fitness. The translational value of these findings empowers family physicians to advocate for policies and community-level changes that improve adolescent fitness and long-term health outcomes.

5.3 Conclusion

This thesis investigated the predictive capability of NBE features in estimating CRF in youth, alongside established predictors including MVPA, BMI, and sex. The findings revealed that NBE features contributed meaningfully to CRF. Importantly, this research highlighted gender differences in the association between NBE features and CRF, which were obscured in the overall analysis.

This thesis also exemplifies the utility of supervised machine learning techniques, such as random forest modelling, to explore complex, nonlinear relationships between neighbourhoods and health outcomes. This method provides an opportunity to integrate sociodemographic, behavioural, and environmental data, offering a more comprehensive understanding of the interplay of factors shaping youth well-being. In addition to providing important perspectives that warrant further investigation, results can also guide interest holders in developing strategies to foster healthier neighbourhoods and enhance fitness outcomes among youth.

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