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Mental health problems in urban neighbourhoods: the role of physical and social environment

vorgelegt von:

Yi-An Liao

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First supervisor: *Prof. Elisabeth Binder*

Second supervisor*:* *Prof. Edward Barker*

Third supervisor: *Prof. Nikolaos Koutsouleris*

Dean: Prof. Dr. med. Thomas Gudermann

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Affidavit

Liao, Yi-An

Surname, first name

Kraepelinstraße 2-10

Street

80804, Munich

Zip code, town

Germany

Country

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Medical Faculty

MMRS

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Liao, Yi-An
Surname, first name

Kraepelinstraße 2-10
Street

80804, Munich
Zip code, town

Germany
Country

I hereby declare that the electronic version of the submitted thesis, entitled

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Place, date

Yi-An Liao
Signature doctoral candidate

Abstract

Humans are surrounded by the outer environments and keep interacting with them. Humans face the challenge of the external world throughout their life course, adapt to the change, and strive to thrive. However, some environmental aspects deteriorate human health and leave sequelae throughout human life.

This thesis uses a theoretical framework, Neighbourhood Mental Health Map, to describe the human-neighbourhood relationship in an ecological way. In line with this framework, the present thesis presents three empirical studies disentangling the complex interactions between human mental health and the physical and social environment in modern urban neighbourhoods. The first two studies were dedicated to the relationship between physical environments and mental health problems, and the third study focused on the social environment and development of adolescent mental health.

In more detail, the first study aimed to identify the syndemic structure of mental problems in the context of urban neighbourhood environments characterized by high nighttime light exposure. The second study sought to identify the physical signatures (i.e., specific geographic patterns) of different mental health problems (e.g., depression, overdrinking). The third study tried to identify the roles of social mechanisms (e.g., social cohesion, informal social control and deviant peer affiliation) and conduct disorder development at varying levels of deprivation.

Abbreviations

ADHD Attention deficit hyperactivity disorder

AIC Akaike Information Criterion

ALSPAC Avon Longitudinal Study of Parents and Children

BIC Bayesian Information Criterion

CCA Canonical correlation analysis

CD Conduct disorder

DAWBA Development and Well-Being Assessment

DMSP/OLS The Defense Meteorological Program/Operational Line-Scan System

DSM Diagnostic and Statistical Manual of Mental Disorders

GEE Google Earth Engine

GGM Gaussian Graphical Model

GMV Grey Matter Volume

HPA Hypothalamic–Pituitary–Adrenal

IMD Indices of multiple deprivation

LCA Latent Class Analysis

LSOA Lower Super Output Area

LTA Latent transition analysis

MODIS Moderate Resolution Imaging Spectroradiometer

msCCA Multiple sparse canonical correlation analysis

NaPTAN National Public Transport Access Nodes

NCT Network Comparison Test

NDBI Normalized Difference Built-Up Index

NDVI Normalised Difference Vegetation Index

NIR Near Infrared

NLE Nighttime light emission

ROI Region of interest

SABIC Sample-size-adjusted Bayesian Information Criterion

SDRC Social Disadvantage Research Centre

sCCA Sparse canonical correlation analysis

SCN Suprachiasmatic Nucleus

SES Socioeconomic status

SWIR Short Wave Infrared

UKBB UK Biobank

UKBUMP UK Biobank Urban Morphometric Platform

VIDDA Violence, Immigration, Depression, Diabetes, and Abuse

VIIRS Visible Infrared Imaging Radiometer Suite

WHO World Health Organisation

Publications

Published

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CHAPTER 1: General introduction

1.1 Mental health in the context of neighbourhood environment

Mental health problems are one of the leading health burdens worldwide (Vos et al., 2015), accounting for more than one-fourth of non-communicable diseases (Prince et al., 2007). Five mental health problems (major depression, anxiety disorders, schizophrenia, dysthymia, and bipolar disorder) were among the leading 20 causes of the global burden of disease in 2013 (Vos et al., 2015). Estimation showed that mental health problems account for 13.0% of disability-adjusted life-years (Vigo et al., 2016). By 2030, depression, one of the most devastating mental health problems, will be the first leading cause of disability (WHO, 2011). Mental health problems are consequences of the interplay between biological (e.g., genetic vulnerabilities) and environmental risk factors. Many studies have examined genetic vulnerabilities, both from twin-biometric and molecular (genome-wide association) perspectives. Studies on environmental influence on mental health have mainly focused on early familial and intimate social environments (e.g., early trauma experience, sex abuse, and parenting style). Less emphasis has been placed on the role of the neighbourhood environment within walking distance and its role in mental health problems. Of interest, however, the neighbourhood has played a crucial role in criminological investigations of child conduct disorder behaviours (i.e., lying, fighting, stealing), adolescent delinquency, crime rates and offender rates (Bruinsma et al., 2013; Jennings et al., 2018).

In childhood, children tend to experience the neighbourhood indirectly through their parents' behaviours (Kohen et al., 2008). Since late childhood and early adolescence, their neighbourhood experience has become more direct. Young people explore the neighbourhood intensively and socialise with their peers in such a context (Matthews & Limb, 1999; Tompsett et al., 2016). As for adults, they constantly perceive cues and receive information while being in the neighbourhood, either when they are engaging in livelihood activities, leisure activities or just walking back home from work.

Different types of neighbourhoods have different typologies and trajectories toward negative mental wellbeings. In a western neighbourhood, negative cues can be quarrels among neighbours, garbage on the street and graffiti on the walls. Such physical and social features perceived in the neighbourhood may play an important role in depression (Kim, 2010). In a rural Indian neighbourhood, residents are bound to the traditional caste system, and residents from lower caste suffer from constant discrimination and are prone to diminished mental health (Gupta & Coffey, 2020; Mathias et al., 2015). In neighbourhoods where conflicts were rampant, e.g., in Vietnam during the Vietnam war and Palestine, witnessing or even experiencing war-related violence in the neighbourhood can have a life-long effect (El-Khodary & Samara, 2020; Kovnick et al., 2021). In neighbourhoods where certain physical features have a particular meaning, e.g., in the Inuit neighbourhoods in Canada, witnessing the shrinking sea ice surface can lead to the so-called “ecological grief” and hence diminished mental health (Cunsolo & Ellis, 2018; Durkalec et al., 2015).

Despite global diversity in the different types of neighbourhoods discussed above, the present thesis will focus on the Western neighbourhoods with modern, industrialised features, i.e., urban neighbourhoods. Urban neighbourhoods have been of particular interest in sociology, criminology, and psychiatry. It is the first time in human history that half of the human population lives in this type of environment, and the phenomena (e.g., inequality, high crime rates, high mental illness incidence) arising in this context need explanations and solutions.

1.1.1 Physical and social risk factors in urban neighbourhoods

According to United Nations, 67% of the world population will reside in urban areas by 2050 (Heilig, 2012). Modern urban areas are very different from cities and towns in agricultural areas and extremely different from our shared evolutionary histories – the hunter-gathering communities. The neighbourhood we are used to in the contemporary era is a product of a relatively recent phenomenon in human history: *urbanisation*. Urbanisation is characterised by a change in size and population density (Vlahov & Galea, 2002). This phenomenon is often resulting from population migration from less-dense areas (e.g., rural areas, countryside) to more-dense areas (e.g., urban areas, cities)(Satterthwaite et al., 2010). Urbanisation has been particularly drastic since the 1800s, the beginning of the industrial revolution (Zhang, 2016). Such movement can be a rational decision considering the advantages in urban environments. For example, cities provide more career opportunities, more accessible health care and better education quality (Chen & Rosenthal, 2008; Das et al., 2012; Reda et al., 2012). Also, cities offer a range of activities that residents can enjoy. However, living in urban neighbourhoods is not without disadvantages and adverse influences on mental and physical wellbeing. For example, heavy traffic in urban areas leads to air pollution in many cities (Han et al., 2015, 2018). High air pollution, e.g., particulate matter 2.5 ($PM_{2.5}$), increases pulmonary, cardiovascular and mental health problems (Dominici et al., 2006; Kim et al., 2016; Pun et al., 2017). Also, the high density of buildings reduces the surface preserved for nature (Pauleit et al., 2005). The natural environment allows residents to engage in physical exercises and social interactions (Hartig et al., 2014). Greenness in the neighbourhood reduces the risk of obesity and type 2 diabetes mellitus (De la Fuente et al., 2021).

As for the social aspects, economic inequality in cities brings about unevenly distributed deprivation, leading to neighbourhood disorder, ghettoisation and the formation of hot spots with high crime rates (Chamberlain & Hipp, 2015). Studies have shown that people living in neighbourhoods with high crime rates (“hot spots”) have more risk of developing depression (Weisburd & White, 2019). Although the causality between hot spots and depression is complex, Weisburd & White (2019) argued the relationship could be multifaceted, including the selection process (i.e., residents with poor health are bound to live in such deprived places) and detrimental influence from the hot spots. As a result, the physical and social environments in an urban neighbourhood are entangled with residents’ wellbeing.

The interest in the association between urban neighbourhoods and mental disorders dates back a century. Faris and Dunham (1939) and Hare (1956) first reported that the rate of schizophrenia is higher in cities than in suburban areas. Two hypotheses were proposed to explain this phenomenon. The “social isolation” hypothesis argued that the social factors present in urban areas led to schizophrenia; on the other hand, the “attraction” hypothesis proposed that such disorganisation nature of city centres attracted residents with the propensity to develop schizophrenia (Hare, 1956).

Since then, a substantial body of literature has reported the association between schizophrenia and residence in urban neighbourhoods (March et al., 2008; Padhy et al., 2014). As for other mental health problems, many studies found that depression and anxiety are more prevalent in urban than rural areas (Kovess-Masféty et al., 2005; Purtle et al., 2019; Romans et al., 2011). Also, some evidence shows that living in urban areas is a risk factor for conduct disorder and antisocial personality disorder (Goulter et al., 2020; Miller et al., 1999)

1.1.2 The definition problem of urbanicity

The definition of “urbanicity” is argued today amongst existing scholars. For example, what features in a geographic area are necessary and sufficient for this area to be categorised as "urban"? Traditionally, urban areas are defined based on the density of the resident population. A substantial body of literature has used population density to establish an urban-rural categorisation to classify land surface; and compared the incidences of mental health problems in these two settings (Marcelis et al., 1998; Sundquist et al., 2004; van Os et al., 2001). Despite its simplicity and use by many studies in the past decades, the reductionist usage of the urban-rural categorisation based on population density prevents us from asking further which particular features in urban or rural areas are associated with mental health problems. High population density is only one of many features within urban neighbourhoods, and not necessarily means a densely built surface. This is because cities are three-dimensional instead of on a one-dimensional scale (Boyko & Cooper, 2011). Also, high population density does not guarantee better access to infrastructure or health care (Trindade et al., 2021). In an impoverished slum, e.g., a slum in Mumbai, the population density can be high, but the basic infrastructure (e.g., safe drinking water supply) can be inadequate (Murthy, 2012). In fact, Das et al. (2021) illustrated that slums in India were specifically vulnerable to COVID-19 due to their inadequate sanitation and high population density. To disentangle the complicated associations between the urban neighbourhood environment and mental health, we need to specify various physical and social features to describe the "urbanicity" in urban neighbourhoods.

1.1.3 Neighbourhood Mental Health Map as the framework for understanding urbanicity

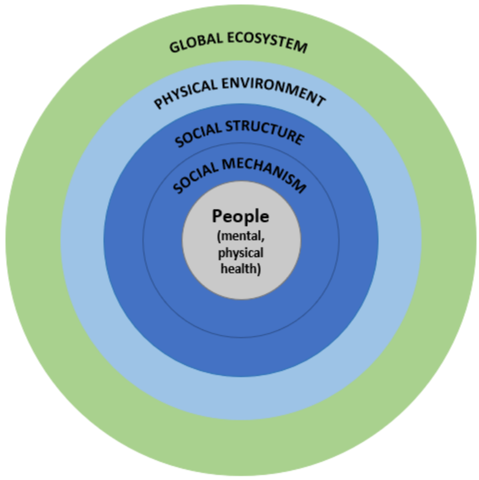
In order to incorporate the physical and social features into the umbrella concept of "urbanicity", this thesis adopts the framework of *Neighbourhood Mental Health Map*, designed based on the *Settlement Health Map framewor*k (Barton & Grant, 2006). The Settlement Health Map framework borrows insights from the ecosystem theory that views neighbourhoods as more than arbitrary human settlements but part of the natural world (Bronfenbrenner, 1986, 2005; Kim et al., 2020). According to the ecosystem theory, the neighbourhoods are both dependent on the natural environment and influence it (Barton, 2005). Integrating the ecosystem framework, Barton further developed the Settlement Health Map to summarise the relationship between human health and neighbourhoods (Barton & Grant, 2006). The Settlement Health Map has eight layers in which “people”s health is in the centre. “People” constantly receive impacts from outer layers encircling them. A layer above “people” is the “lifestyles”. The “lifestyles”, in turn, are not totally a personal choice but can be influenced by the outer layers, including the social capital and social networks in the “community”. Whether the social capital (i.e., sense of community, collective action for one goal) and social networks (i.e., interpersonal, informal relationships among neighbours) are viable depends on the outer “local economy” and the “activities” (e.g., different infrastructures) the neighbourhood can provide (Barton et al., 2021, p.116).

Together with “people”, these layers are surrounded by the built physical environment, “built environment”, which, in turn, is embedded in the broader “natural environment”. Finally, the whole system is buried in the “global system”, which receives the influence at a global scale, e.g., climate change. However, it should be noted that these layers represent a process rather than a state, and each layer can interact with other layers (Barton & Grant, 2006; Barton, 2005).

Generally speaking, the Settlement Health Map suggests that humans and their wellbeings are embedded in the social environment (i.e., lifestyles, community, local economy, activities), which is, in turn, buried in the physical environment (i.e., built and natural environment). Hence, we adapted the Settlement Health Map and created the Neighbourhood Mental Health Map (**Figure 1.1**) to fit the purpose of the present thesis. In the Neighbourhood Mental Health Map, “people’s wellbeing” is the innermost sphere, encircled by the two social environment layers: “social mechanism” and “social structure”, which is, in turn, buried in the “physical environment”. The “social mechanism” layer corresponds to the “lifestyles” and “community” layers because they include the interactions with neighbours. The “social structure” corresponds to the original “local economy” and “activities” because they characterise the neighbourhood-level socioeconomic status and various resources a neighbourhood can provide. Finally, “physical environment” encompasses the original “built environment” and “natural environment”.

The three studies presented in this thesis examine how different layers interact with peoples’ mental and physical health.

Figure 1.1

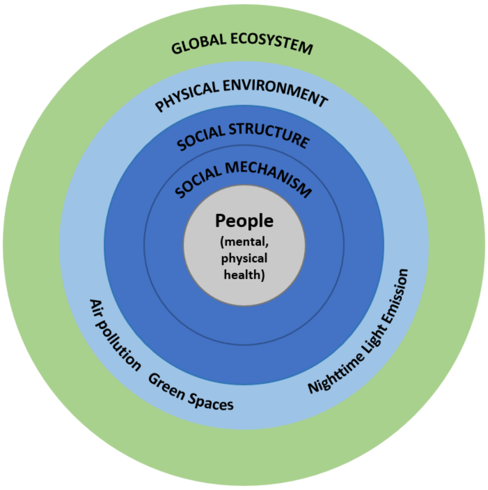


Note: The Neighbourhood Mental Health Map is designed based on the Settlement Health Map (Barton & Grant, 2006)

1.2 Physical environment in urban neighbourhoods

1.2.1 Physical features in urban neighbourhoods

Figure 1.2



Note: Physical Environment in the Neighbourhood Mental Health Map contains visible (e.g., green spaces, nighttime light emission) and non-visible physical features (air pollution).

We will start from the outer layer, the physical environment in an urban neighbourhood (**Figure 1.2**). The thesis adopts a broader definition of the physical environment that includes but is not limited to natural features and buildings. The physical environment includes visible (e.g., greenness, nighttime light emission, built-up surface) and non-visible features (e.g., air pollution, noise) and features that can be quantified using geographic measurements (e.g., the density of shops, distance to a service). The physical environment in urban areas differs largely from that in rural areas. For example, in order to accommodate the dense population, urban neighbourhoods are usually characterised by buildings that shrink the surface preserved for nature (Capello & Camagni, 2000; Chen et al., 2008; De Bellefon et al., 2021; Jim, 2004; Tan et al., 2005). The lack of green spaces makes urban areas more vulnerable to air pollution and the heat island effect (Jaung et al., 2020; Selmi et al., 2016).

The urban areas are also characterised by a high density of facilities and services to meet the need of the increasing population (Chen et al., 2008).

1.2.2 Review of current methods to assess the physical environment

Until recently, studies on urban neighbourhoods with noxious physical features mainly used three methods (or a combination of them) to assess the neighbourhood's physical environment: self-report individual perception, ground-level approach and satellite approach. The first way to evaluate the physical environment is to ask the individuals about their subjective opinions, either by questionnaires, in-person interviews or telephone surveys (Cerin & Leslie, 2008; Sooman & Macintyre, 1995; Wen et al., 2006; Wilson et al., 2004). For example, Wilson et al. (2004) designed a range of questions to inquire about residents' perception of the physical features in their neighbourhoods. Typical answers regarding greenness and neighbourhood resources can be: "It's got trees…it's actually green" and "I like the amenities and transportation is so convenient." (Wilson et al., 2004). However, this method risks so-called same-source bias. For example, residents with depression propensity are more inclined to perceive the outer environment as hostile, harmful and threatening (Chum et al., 2019).

Another way is to utilise a range of ground-level data. Sarkar et al. (2015) registered the participants of UK Biobank to a range of census-based data (AddressBase Premium databases, National Public Transport Access Node, Ordnance Survey Mastermap, UK Land Registry and UKMap) and created an Urban Morphometric Platform. The usage of ground-level data allows a more objective assessment of a given neighbourhood and is free from the same-source bias when researching mental health. Nevertheless, collecting this data requires detailed plans, consistent funding, cutting-edge technology and efficient authority. Not every country is capable of organising and proceeding with this type of data collection. Therefore, such study results are hard to apply to other countries and compare in an international context.

The third possibility is to use data collected by remote sensing technique, i.e., satellite. Satellites detect the light reflected by the earth's surface and have been recording the change in the earth's surface for decades. It has witnessed an unprecedented change in the ecosystem and demographics throughout human history. Geographers have developed indexes to describe different physical features based on the detected reflected light and the knowledge of the ground-level surface. For example, the Normalised Difference Vegetation Index (NDVI) is derived to capture the green coverage because we know that green vegetation absorbs red light and reflects infrared light. Therefore, the green coverage can be estimated by calculating the difference between reflected red light and infrared light. Another useful satellite index is the Normalized Difference Built-Up Index (NDBI) to evaluate the human settlement. Some studies made use of NDVI and identified the protective association between residential greenness and depression, and anxiety (Banay et al., 2019; Di et al., 2020; Hartley et al., 2021; Sarkar et al., 2018). Other studies developed their satellite index, which summarises urbanicity, and found a positive correlation between urban areas and depressive symptoms (Xu et al., 2022).

1.2.3 Mental health problems in urban neighbourhoods with the detrimental physical features: Current research

In the following sections, we will introduce three important physical features in urban areas and their relationships with mental health: reduced green spaces, air pollution and nighttime light emission.

1.2.3.1 Reduced green spaces

In many countries, densely built-up surface reduces access to and the amount of available natural environment, particularly the green spaces (Capello & Camagni, 2000; Chen et al., 2008). With rapid urbanisation in the past century, many countries have seen a dramatic drop in green spaces within the cities. Pauleit et al. (2005) used aerial photographs to compare green space changes between 1975 and 2000 in Merseyside, UK. The study revealed that in all 11 investigated sites, there had been a loss of green space during the last 25 years (Pauleit et al., 2005). In Brasil, urbanisation has led to the fragmentation and reduction of green spaces in cities (Benchimol et al., 2017). Another burgeoning metropolitan area, Beijing, has also faced a similar issue. Between 2000 and 2010, Bejing lost almost 200 km^2 of green space (Zhang et al., 2015). The reduction of green space is associated with higher mental health problems. Spending time in green spaces grants restorative benefits, reduces stress, protects against depression and other psychological distress, and even lowers salivary cortisol concentration (Kellert & Wilson, 1993; Maller et al., 2006; Park et al., 2010; Thompson et al., 2012). Some studies argue that this correlation is mediated by physical activity in green spaces (Dzhambov et al., 2018). Green spaces also provide residents with opportunities for socialisation, which benefits mental health (Bedimo-Rung et al., 2005; Chiesura, 2004; Kuo et al., 1998; Wolch et al., 2014). Recently, the role of biodiversity has received attention. Green spaces are essential for maintaining biodiversity in urban areas. A mice study showed that diverse airborne microbe exposure could reduce anxiety-related behaviours, potentially through the modulation of gut flora (Liddicoat et al., 2020). Indeed, the diverse microbiomes are believed to modulate and strengthen the immune system and improve human wellbeing, including mental health (Kelly et al., 2016; Liddicoat et al., 2016; Rook, 2013; von Hertzen et al., 2011).

1.2.3.2 Air pollution

According to WHO, seven million people die each year because of air pollution (WHO, 2021). Urban areas are also characterised by decreased air quality. Traffics and industrial activities in cities lead to the emission of waste gas and particles (e.g., CO, NO2, $PM_{2.5}$, PM_{10}, SO2)(Querol et al., 2004; Zheng et al., 2017). Small particles are closely related to diminished physical health, especially in the cardiovascular and respiratory systems (Kelly & Fussell, 2015; Manisalidis et al., 2020; Xing et al., 2016). Recently, studies also found an association between long-term exposure to air pollution (e.g., $PM_{2.5}$) exposure and depression (Kim et al., 2016; Kioumourtzoglou et al., 2017). Also, short term exposure to air pollution is associated with higher admission due to depression (Gu et al., 2020). As for adolescents, a study found that exposure to air pollution at the age of 12 is correlated to depression at the age of 18 (Roberts et al., 2019). Although the underlying mechanism is still poorly understood, it is considered that neuroinflammation plays an essential role. Inflammation is considered to associate with mental health problems, e.g., depression, bipolar disorder, and obsessive-compulsive disorder (Miller & Raison, 2016; Najjar et al., 2013). The overactivity of IL-6, one of the inflammation markers, is associated with higher suicidality (Kappelmann et al., 2021). Small particles from air pollution are able to reach the brain via the olfactory pathway, causing inflammation in the central neural system (Calderón-Garcidueñas et al., 2008; Levesque et al., 2011).

1.2.3.3 Nighttime light emission

Another feature that characterises urban areas is nighttime light emission (NLE). In the past, humans were used to dimming light at night. A full moon can merely reach the illumination of 0.1 to 0.3 lux at night (Gaston et al., 2013). The invention of electric light in the late 19th century dramatically increased the amount of light at night people could expose to. The electric light enables humans to extend working hours and other leisure activities into the night. Since the last century, artificial light usage has seen rapid growth around the world, especially in urban areas (Cinzano et al., 2001). Organisms, however, are not evolutionarily equipped to adapt to excessive light at night. Apart from intrinsic circadian rhythm, organisms need an external cue (i.e., zeitgeber) to adjust and synchronise with the environment. In humans, for example, the external light/dark cycle is received first at the photosensitive retinal ganglion cells and transmitted to the suprachiasmatic nucleus located in the hypothalamus (Berson et al., 2002). The information travels further down to regulate various kinds of hormones, including melatonin, glucocorticoid, insulin and leptin (Albreiki et al., 2017; Kalsbeek et al., 2001; Son et al., 2011). The suprachiasmatic nucleus also projects axons to brain regions involved in emotion, e.g., prefrontal cortex (Sylvester et al., 2002). This anatomical architecture implies a link between the light/dark cycle and mental health. A meta-analysis of 11 studies showed that disrupted light/dark cycle (e.g., shift work) is associated with increased depression risk (Lee et al., 2017). Also, exposure to light at night is associated with depressive symptoms, anxiety and suicidal ideation or attempt (Min & Min, 2018; Paksarian et al., 2020).

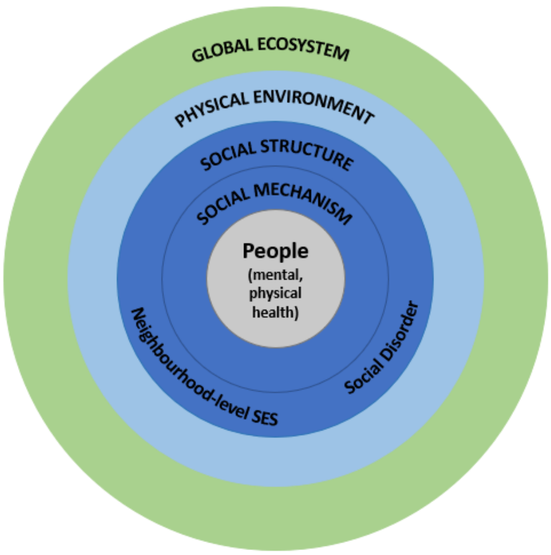
Although a substantial body of studies has shown the interactions between the physical environment and mental health, most studies focused on a specific physical feature (e.g., green spaces). However, urban features often co-occur, and humans are exposed to these physical features (e.g., lack of green spaces, air pollution) as a whole rather than to a specific feature. Also, these physical features are often interrelated, which leads to the difficulty of isolating the single effect of a particular feature. Therefore, there are still gaps in our understanding of how these physical environment features interact with mental health.

In this thesis, we investigated how the physical environment in urban areas interacts with mental health problems. More specifically, in **Chapter 3**, we investigated how NLE is correlated with other urban features and mental health problems. In **Chapter 4**, we sought to identify the satellite-derived physical signatures of different kinds of mental health problems.

1.3 Social structure and social mechanism in urban neighbourhoods

1.3.1 Social structure in urban neighbourhoods: neighbourhood-level socioeconomic status and neighbourhood disorder

Figure 1.3



Note: Social structure includes neighbourhood-level socioeconomic status (SES) and social disorder.

In the Neighbourhood Mental Health Map, the layers below the physical environment are the embedded social environment, which has two components: the outer layer *social structure* and the inner layer *social mechanism*. In this thesis, we defined *social structure* as a set of social arrangements which form a society as an entity (Deji, 2011, p71).

Social structure is multidimensional and includes many components. Ethnicity, segregation, resident turnover, hierarchies, and cultural norms are all part of the neighbourhood social structure. Here, we introduce two examples of social structure: *neighbourhood-level socioeconomic status (SES)* and *social disorder* (**Figure 1.3**). SES can be assessed at the individual and neighbourhood levels. Whereas individual-level SES often refers to household income, neighbourhood-level SES includes average income and other social structural indicators (e.g., unemployment rate and welfare dependency rate). In the literature, low neighbourhood-level SES often serves as the working definition of *deprivation* of a neighbourhood (Visser et al., 2021).

For decades, researchers have been linking neighbourhood-level SES and residents' physical and mental wellbeing. Residents living in socioeconomically deprived areas are subject to mental health problems and have more health-risk behaviours (Algren et al., 2018). For example, residents living in such deprived areas tend to smoke and have a low intake of fruits and vegetables than the general population (Algren et al., 2018). Also, in such socioeconomically deprived neighbourhoods, more stores provide low-quality food at a low price (Tach & Amorim, 2015). This creates a vicious cycle in which residents' wellbeings deteriorate. As for children, the impact of neighbourhood-level socioeconomic status begins at birth. Low neighbourhood-level socioeconomic status is associated with adverse birth outcomes (Meng et al., 2013). Also, with exceptions (Barr, 2018; Dunn et al., 2015; Ma & Klein, 2018), it has been shown that children exposed to low neighbourhood-level socioeconomic status have more mental problems (Astell-Burt et al., 2012; Jonsson et al., 2018; Kohen et al., 2009; Martinez & Polo, 2018).

However, it should be noted that there is no consensus on what aspects should be included when assessing deprivation. Although previous studies often focused on the SES aspect of deprivation, in the literature, deprivation can also mean a lack of public resources, poor housing and disorder in neighbourhoods (e.g., perceived danger or high crime rate, Visser et al., 2021). Therefore, in this thesis, we defined *deprivation* as the state of disadvantaged social structure which includes multifaced features (e.g., neighbourhood-level SES, social disorder, education, housing etc.).

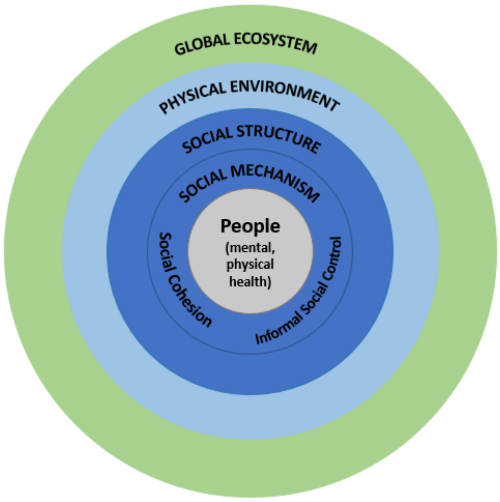
Social disorder focuses on the breakdown of the order in a given neighbourhood. It is characterised by observable cues, like rubbish, graffiti, abandoned vehicles and buildings, and loitering (Polling et al., 2014; Ross & Jang, 2000). Such cues convey to the residents that delinquencies in the given neighbourhood are neither monitored nor sanctioned (Wilson & Kelling, 1982).

Residents in such environments often feel unsafe, perceive high crime rates, and such fear, via physiological mechanisms, could deteriorate physical and mental wellbeings (Ross & Mirowsky, 2001). For decades, many studies have been using perceived danger (or safety) or objective crime rates to assess the level of neighbourhood disorder (Polling et al., 2014; Visser et al., 2021). Some activities, e.g., graffiti and soliciting, are minor crimes and can be perceived as signs of neighbourhood disorder. Some scholars argue that neighbourhood disorder and crime can be regarded as two facets of the same phenomenon (Sampson & Raudenbush, 2001). Living in neighbourhoods with high neighbourhood disorders is related to poor physical and mental health (e.g., depression)(Botchkovar et al., 2018; Lorenc et al., 2012; Stafford et al., 2007). As for children, with a few exceptions (Dupéré et al., 2012; Huang et al., 2015; Jonsson et al., 2018), it has been reported that high neighbourhood disorder is associated with increased internalising and externalising mental health problems

(Barr, 2018; Bush et al., 2010; Lawler et al., 2017; Li et al., 2017; Milam et al., 2012; Singh & Ghandour, 2012).

1.3.2 Social mechanism in urban neighbourhoods: social cohesion, informal social control

Figure 1.4



Note: Social mechanism includes social cohesion and informal social control.

Although a substantial body of literature linked neighbourhood-level SES and neighbourhood disorder to diminished mental wellbeing, some reported that social capital (i.e., supportive networks consisting of friends, family, colleagues, with whom one can discuss personal matters) and interpersonal interaction also play a more crucial role (Visser et al., 2021). This comes to the inner layer of the social environment, i.e., the social mechanisms (**Figure 1.4**). In this thesis, we defined *social mechanism* as recurring, interpersonal patterns of social interaction within a specific social structure.

The idea of differentiating social structure and social mechanism comes mainly from criminological studies. It has been indicated that social structure itself, e.g., low neighbourhood-level SES, might not directly cause crime, but rather crime happens mainly in neighbourhoods where social mechanisms are disrupted (Gau, 2014; Sampson et al., 1997).

More specifically, the link between social structure and neighbourhood outcomes is mediated by the patterns of social interactions between the residents in neighbourhoods (Sampson et al., 1997). In the same vein, the social mechanism can also play an important role between social structure and mental health. Two social mechanisms have been extensively investigated over the last decades: *social cohesion* and *informal social control* (**Figure 1.4**). In this thesis, we defined *social cohesion* as mutual trust, the interconnectedness between neighbours in a neighbourhood (Gau, 2014). Social cohesion is often characterised by a friendly atmosphere and readiness to help neighbours. In neighbourhoods with high social cohesion, residents are familiar with each other, willing to help each other and have a tight social bond (Gau, 2014). Residents in such neighbourhoods perceive less stress, more safety and are more satisfied with their lives (Grogan-Kaylor et al., 2006).

On the other hand, *informal social control* indicates the collective mobilisation of the neighbourhood. In more detail, in neighbourhoods with high informal social control, residents are more willing to supervise the community and intervene in harmful or suspicious behaviours (i.e., adolescents loitering around) for the common good. Some studies further differentiated informal social control into direct and indirect forms (Gau, 2014; Warner, 2007). In the direct form, residents intervene directly in the quarrel, fighting, delinquency or other misbehaviours. In the indirect form, residents contact external authorities (e.g., police) to intervene. It should be noted that despite the involvement of authorities, the action (e.g., calling the police) is still considered informal because the residents do not possess juridical power. These two forms of informal social control differ qualitatively, and neighbourhoods with different social structures might prefer one over another (Gau, 2014).

Apart from its role in the general neighbourhood outcomes, social cohesion and informal social control also play an essential role in mental health. Regardless of the deprivation level, residents living in high social cohesion and informal social control reported higher overall physical and mental wellbeing (Browning & Cagney, 2002). Most studies found that high social cohesion is associated with low depression (Echeverría et al., 2008; Gary et al., 2007; Mair et al., 2009). As for children, studies have found that lower social cohesion is correlated with increased internalising and externalising problems (Elgar et al., 2010; Eriksson et al., 2012; Novak & Kawachi, 2015; O'Campo et al., 2010; Oberle et al., 2011; Visser et al., 2021). Also, a high level of social cohesion and informal social control can protect children from developing externalising problems in deprived neighbourhoods (Odgers et al., 2009).

1.3.3 Conduct disorder in the context of social structure and social mechanism: Current research

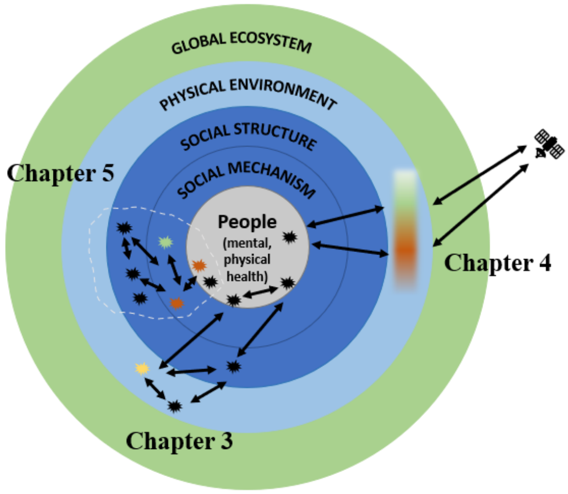
In **Chapter 5** of this thesis, we investigated how social mechanism interacts with children's one of the most burdensome mental health problems, namely the conduct disorder (CD) behaviours, in the context of different social structures.

According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), CD behaviours are repetitive and persistent behaviours that violate the widely accepted social norms (American Psychiatric Association, 2013). CD behaviours include a range of property delinquency, e.g., stealing, breaking into others' property, and physical violence. CD is of significant interest because it leads to costly social consequences and burdensome mental health problems. CD can both negatively impact the lives of others as well as disrupt an individual's life opportunities. For example, CD behaviours at a young age can predict continued co-occurring mental health problems (e.g. ADHD, depression), criminal behaviours, violence and substance use in adulthood (Erskine et al., 2016; Mordre et al., 2011; Odgers et al., 2008). Adults with persistent CD behaviours in childhood account for more than half of all convictions and 25% of monthly welfare benefits (Rivenbark et al., 2018). The Global Burden of Disease Study 2010 showed that CD is one of the leading causes of disability in children (Erskine et al., 2014). As with most mental health problems, the aetiology of CD is complex and is an interplay between genetic predispositions and the environment (Azeredo et al., 2019; Cecil et al., 2018; Fairchild et al., 2019). Nevertheless, not all children with hereditary predispositions to CD develop CD behaviours later in life. Many studies strive to identify the environmental risk factors that are associated with CD. One of the most extensively researched environments is the familial environment. Poor parenting, low household economic status, parental criminality, parents' drug use, domestic violence, lack of supervision, and discipline are associated with CD various (Barker et al., 2011; Frick & Dickens, 2006; Murray & Farrington, 2010; Yockey et al., 2021).

Other studies investigated the roles of social structure (i.e., neighbourhood-level SES) and the embedded social mechanism (collective efficacy: social cohesion and informal social control)(Gau, 2014; Fairchild et al., 2019). Indeed, low neighbourhood socioeconomic status and high neighbourhood disorder are both associated with high CD behaviours (Beyers et al., 2001; Martinez & Polo, 2018). Also, high social cohesion and informal social control can protect children and adolescents from developing CD behaviours (Mrug & Windle, 2009; Odgers et al., 2009; Pei et al., 2020; Sharma et al., 2019). Nevertheless, these studies often adopted a cross-sectional perspective, and it is still not clear how CD behaviours interact with the social mechanism in the context of social structure longitudinally.

1.4 Aims of the thesis

Figure 1.5



Note: The role of **Chapters 3**, **4** and **5** in the Neighbourhood Mental Health Map**.** (Yellow asterisk: nighttime light emission; green asterisk: protective factor; orange asterisk: risk factor; black asterisk: symptoms and factors in different layers; colour bar: reflected light detected by satellites)

This thesis aimed to investigate the interaction between urban physical, social environments and the mental wellbeing of adults and adolescents (**Figure 1.5**). We used different geographical data (census level data, deprivation index, satellite product data, satellite raw data etc.) and multidimensional statistical methods to disentangle these complicated relationships. We first focused on the association between the physical environment in the urban neighbourhood and the general population's mental wellbeing. Then, we turned to young people, studying how urban neighbourhoods' social environment interacts with their development.

In more detail, in **Chapter 3**, we studied one of the most prominent urban features in industrialised society, i.e., the nighttime light emission, and asked how are nightlight and other urban features associated with mental health in the general population. In **Chapter 4**, without selecting any particular urban features, we tried to look for the specific physical signatures of depression, anxiety, and substance use behaviour using satellite raw data and discuss the perspective of further usage of this approach. In **Chapter 5**, we studied how children and adolescents interacted with their neighbourhood and explored how social mechanism interacts with adolescent conduct disorder in different social structures.

CHAPTER 2: Study samples, environmental measures, and statistical methods

The purpose of **Chapter 2** is to illustrate the rationale for choosing study samples, environmental measures and the statistical methods in the corresponding studies.
The behavioural measures, analytical pipelines and specific methodological details are discussed in the method sections in the chapters dedicated to each project: **Chapter 3**, **4** and **5**.

2.1 Study samples

2.1.1 UK Biobank

The UK Biobank (UKBB) was used in studies on the neighbourhood's physical environment and mental health. These studies are discussed in detail in **Chapter 3**, and **Chapter 4**. UKBB is an ongoing population-based cohort including more than 500,000 adults who live in the United Kingdom (UK). UKBB started to recruit participants in 2006 and completed the recruiting in 2010. Since 2012, the data has been available for all bonafide researchers.

UKBB aimed to sample the general population living in the UK. However, the response rate is 5.5 %. Also, analyses have shown that respondents compared with the general population, are less likely to live in deprived areas and have fewer health-risk behaviours (e.g., alcohol intake and smoking) and self-reported physical health problems (Fry et al., 2017).

There are three important advantages of using UKBB in this thesis, especially for the studies on the associations between the physical environment and mental health problems discussed in **Chapter 3** and **Chapter 4**. First, UKBB provides information on the geographical location based on each participant's home address, which is essential to assess the neighbourhood-level physical environmental characteristics. The geographical location information is recorded as east and north coordinates. It should be noted, however, that all coordinates were rounded to 1km for data protection. The availability of geographical location coordinates allows researchers to utilise data derived from the satellite analysis (see the method section in **Chapter 3** and **Chapter 4**).

The second advantage of UKBB is that UKBB is linked to the UK Biobank Urban Morphometric Platform (UKBUMP, described in **2.2.3**)(Sarkar et al., 2015), which can be used in tandem with the location information described above. The generation of urban morphometrics is based on a range of UK spatial databases. For example, in land-use morphometrics, the density of health-promoting/inhibiting facilities (e.g., medical services, community services, parks) is derived from the UK Ordnance Survey AddressBase Premium and National Public Transport Access Nodes dataset (Sarkar et al., 2015). The street-level accessibility is based on UK Ordnance Survey Integrated Transport Network (Sarkar et al., 2015). The combination of these datasets captures the geographic characteristics to a great extent and allows researchers to investigate the relationship between environment and mental problems from different perspectives. Also, such data can validate or interpret the results gained with satellite raw data (**Chapter 4**).

Third, UKBB includes a wide range of physical and mental measures, biochemical variables and brain imaging data that allow researchers to investigate psychopathology in a multidimensional manner.

The ethical approvals of UKBB were received from the North West Multi-centre Research Ethics Committee, the Community Health Index Advisory Group, the Patient Information Advisory Group, and the National Health Service National Research Ethics Service. Readers can find the cohort descriptions and study design elsewhere (Sudlow et al., 2015).

2.1.2 Avon Longitudinal Study of Parents and Children (ALSPAC)

The study described in **Chapter 5** in this thesis utilized the Avon Longitudinal Study of Parents and Children (ALSPAC), which is also termed the "Children of the 90s" study (Boyd et al., 2013; Fraser et al., 2013). Eligible participants were all pregnant women living in the greater Bristol area in the United Kingdom, whose delivery dates were estimated between 1st April 1991 and 31st December 1992. In more detail, 14,541 pregnant women were recruited, which gave birth to 14,062 live-born children. From the live birth, 13,988 children survived the first year. When the oldest children reached the age of seven, ALSPAC bolstered the sample with eligible cases who had not joined the cohort. As a result, the data include 15,454 pregnancies, resulting in 15,589 foetuses, and 14,901 of which were alive at one year of age. The ALSPAC Ethics and Law Committee and the Local Research Ethics Committees (NHS Haydock REC: 10/H1010/70) granted the ethical approval. Informed consent for the use of data collected via questionnaires and clinics was obtained from participants following the recommendations of the ALSPAC Ethics and Law Committee at the time. The study website contains details of all the data that is available through a fully searchable data dictionary and variable search tool (webpage: http://www.bristol.ac.uk/alspac/researchers/our-data/).

ALSPAC has at least three features that are of particular benefit for the study on the longitudinal environment-health study. First, as an ongoing multigenerational cohort, ALSPAC contains frequent assessments between birth and age 18 (Boyd et al., 2013). Second, the ALSPAC is a multi-informant cohort that collects data from the caregiver, the child, and clinical staff. This feature is particularly important in the conduct disorder study described in **Chapter 5**. During adolescence, the information on deviant peer affiliation and delinquency from the children themselves can be more accurate than from their caregivers. Third, ALSPAC is linked to the official census record, including the information on deprivation, i.e., indices of multiple deprivations (IMD, described in **2.2.4**). This feature allows researchers to study mental health in the context of objective deprivation levels. The data details are available in the data dictionary provided on the study website. http://www.bristol.ac.uk/alspac/researchers/data-access/data-dictionary/.

2.2 Measures for environment

This section is dedicated to the main variables used to capture the features of the physical environment and social environment. This includes two satellite-measured data used in UK Biobank related projects: (1) Nighttime Light Emission (**Chapter 3**), (2) Satellite raw data (**Chapter 4**); one ground-level measured data used in UK Biobank related projects: (3) UKBUMP (**Chapter 3** & **Chapter 4**); and one deprivation dataset used in ALSPAC related project (4) IMD data (**Chapter 5**). Other measures used in these three studies, including risk factors, behavioural outcomes and covariates, are described in their respective chapters. The dataset and measures for environment are listed in **Table 2.1**.

Table 2.1. Dataset, measures for environment and statistical methods used in each chapter.

		CHAPTER 3	CHAPTER 4	CHAPTER 5
DATASET	UKBB	x	x	
	ALSPAC			x
MEASURES FOR ENVIRONMENT	Nighttime Light Emission	x		
	Satellite raw data		x	
	UKBUMP	x	x	
	IMD	x†		x
STATISTICAL METHODS	sCCA		x	
	msCCA	x	x	
	Network analysis	x		x
	LTA			x

† The IMD information is also incorporated in UKBUMP. However, the IMD information in UKBUMP is limited to 2008 and 2010/2011 (Sarkar et al., 2015)

2.2.1 UKBB Geographic data

2.2.1.1 Geo-position data

The location information of each participant is established based upon the postcode linked to their home address and was converted to east and north coordinates in the Ordnance Survey reference. Of note, such information was rounded to the nearest 1 km for data protection reasons. The east and north coordinates were then converted into geographic longitude and latitude for further data preparation (e.g., satellite measures).

2.2.2 Satellite measures

2.2.2.1 Nighttime light emission (NLE)

Nighttime light emission (NLE) used in **Chapter 3** was based on the data collected by sensors on the Defense Meteorological Program/Operational Line-Scan System (DMSP/OLS), which is prepared by the Earth Observation Group of the Payne Institute for Public Policy, Colorado School of Mines (Baugh et al., 2010; Elvidge et al., 1997). Originally, the OLS sensors are employed to detect the cloud distribution and cloud-top temperatures. However, they are also used to detect visible and near-infrared light emissions during nighttime (e.g., city lights and gas flares)(Croft, 1973). The application of data from OLS includes monitoring population growth, socio-economic activity, human settlements, energy consumption and the ecological footprint of human activity (Huang et al., 2014; Small et al., 2005). Every 24 hours, each OLS can capture every location on the Earth's surface, with a swath width of ~3000 km and a spatial resolution of 30 arc seconds (1km). The digital number of the calibrated light intensity ranges from 0 to 63. In **Chapter 3**, the NLE data relies on DMSP/OLS observations extracted from the Google Earth Engine (GEE) (https://earthengine.google.com/).

2.2.2.2 Satellite raw data

Satellite raw data is used in the project presented in **Chapter 4**. Unlike NDVI, NDBI (described in **Chapter 1**), which are the calculated products of different bands (e.g., NDVI = $\frac{\text{NIR}-\text{Red}}{\text{NIR}+\text{Red}}$, NDBI = $\frac{\text{SWIR}-\text{NIR}}{\text{SWIR}+\text{NIR}}$), the satellite raw data refers to the original reflectance value of each band (e.g., red, NIR, SWIR). Theoretically, the usage of satellite raw data allows researchers to discover satellite-detectable physical signatures (i.e., the combinations of bands) of features of land use, human activity and even health outcomes. The satellite raw data from Moderate Resolution Imaging Spectroradiometer (MODIS) was used in this thesis. MODIS covers 36 spectral bands with the wavelength from 0.4 μm to 14.4 μm (https://modis.gsfc.nasa.gov/about/design.php), in which 18 bands were used in **Chapter 4**. The satellite raw data is extracted from the Google earth engine (GEE), which is a platform providing satellite imagery and geospatial datasets with planetary-scale analysis for scientists. (https://earthengine.google.com/).

2.2.3 UK Biobank Urban Morphometric Platform (UKBUMP)

UK Biobank Urban Morphometric Platform (UKBUMP) is one of the first urban morphometric platforms that address the challenges in urban health study. According to Sarkar et al. (2015), the main flaws in the previous studies include the lack of standardized objective measures for the built environment and the usage of census-based administrative boundaries. The administrative boundary does not necessarily correspond to the neighbourhood in which the individual engages with daily activities. UKBUMP has three advantages that benefit urban health study. First, UKBUMP defines neighbourhood with the area around participants' home location to avoid the arbitrariness of administrative boundaries for the neighbourhood. Second, UKBUMP links the UKBB to multiple national-level spatial datasets, including UK Ordnance Survey Address Base Premiumis, National

Public Transport Access Nodes (NaPTAN) dataset, and Index of Multiple Deprivation (IMD), which allows researchers to investigate the environmental impact from various perspectives. Third, with the origin-destination cost matrix algorithm, UKBUMP measures the accessibility of different neighbourhood destinations (e.g., health care, parks), allowing researchers to assess the neighbourhood functionality objectively. In this thesis, UKBUMP is used in two ways. In **Chapter 3**, UKBUMP is used as the data source of urban features. In **Chapter 4**, UKBUMP data serves as an interpretation tool for the satellite-derived physical signatures.

2.2.4 Indices of multiple deprivations (IMD)

ALSPAC is linked to the Indices of multiple deprivations (IMD), which is provided by the Ministry of Housing, Communities & Local Government. In England, the IMD is calculated by the Social Disadvantage Research Centre (SDRC) at the Department of Social Policy and Social Work at the University of Oxford (Noble et al., 2004, 2008). The IMD is used as the main sociostructural descriptor in **Chapter 5**. In **Chapter 5**, two comparable IMDs, i.e., IMD 2004 and 2007 are used. The reason for using these IMDs is because they are more informative and precise than previous IMDs (e.g., IMD 1998 and IMD 2000) in three ways. First, IMD 1998 and IMD 2000 are based on wards of April 1998, whereas IMD 2004 and IMD 2007 are based on Lower Super Output Area (LSOA), which has a higher resolution. Second, compared to IMD 1998 and IMD 2000, IMD 2004 and IMD 2007 have an independent domain for crime, resulting in seven domains: (1) income, (2) employment, (3) health deprivation & disability, (4) education, skills & training, (5) barriers to housing & services, (6), crime (7) living environment. Each domain is based on information from multiple sources. For example, the income deprivation in IMD 2004 is based on information from Income Support households, Income Based Job Seekers Allowance, Working Families

Tax Credit, Disabled Person's Tax Credit, and National Asylum Support Service (Noble et al., 2004). Crime deprivation in IMD 2004 is based on information from Police Force data on burglary, theft, criminal damage and violence (Noble et al., 2004). Third, the weightings of domains to generate the overall IMD score have been revised since IMD 2004 (Kinsella, 2007).

The deprivation score of each domain is first calculated. The higher the score, the higher the deprivation level in such domain is the specific area. However, the scores cannot be compared across domains since they have different maximum and minimum. Therefore, the domain deprivation scores are ranked. The area with the highest deprivation score is assigned with 1 and the area with the least deprivation score is assigned with 32,482 (Noble et al., 2004, 2008). The rank of the domain score underwent a weighted exponential transformation and summed up to the overall IMD score (Noble et al., 2004, 2008).

However, it should be noted that in **Chapter 5**, instead of using the overall IMD score and rank, the information on the original domain rank is used. In ALSPAC, in order to minimize the risk of disclosure, the original ALSPAC domain ranks were transformed into quantiles ranging from 1 (the least deprived) to 5 (the most deprived).

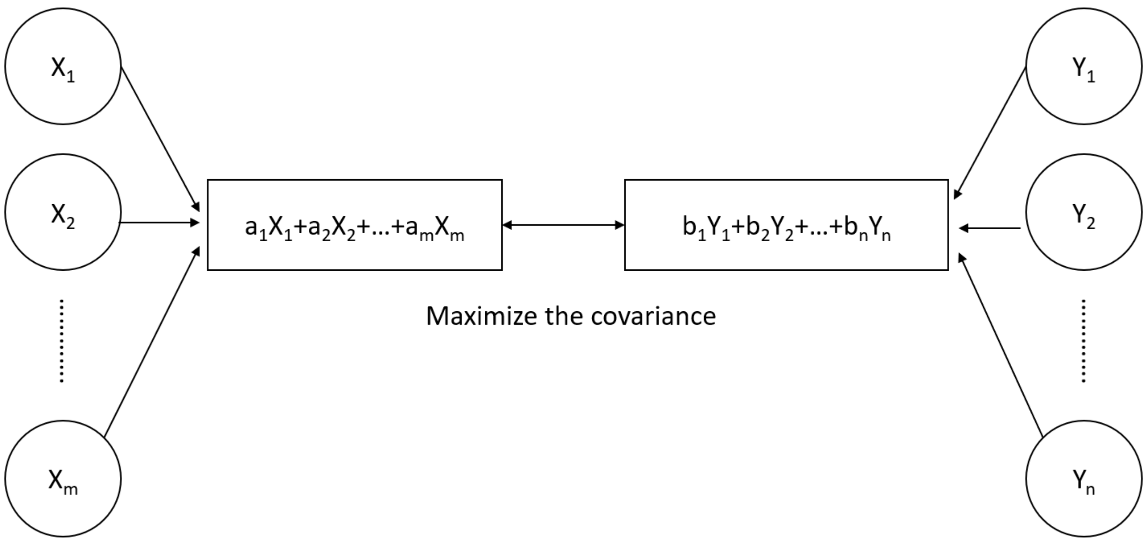
2.3 Statistical methods

The statistical methods used in each chapter are listed in **Table 2.1**. The rationale and advantages of choosing these statistical methods and the general description are presented in this section. The technical details and analytical pipelines are discussed in the method section in **Chapter 3**, **4** and **5**.

2.3.1 Sparse and multiple sparse canonical correlation analysis (sCCA, msCCA)

Canonical correlation analysis (CCA) is a statistical method used to assess the linear association between two variable sets (**Figure 2.1**, X_1, X_2 … Xm and Y_1, Y_2…Y_n, Hotelling, 1936). CCA aims to achieve the maximum of the correlation by maximizing the covariance of the weighted sum of each set. In **Figure 2.1**, the linear combination of the first set of variables (X_1, X_2…X_m) and the second set of variables (Y_1, Y_2…Y_n) are correlated the most if each set takes the loadings of a_1, a_2, …., a_m and b_1, b_2, …, b_n. Using CCA allows researchers to understand how two sets of variables are correlated (e.g., environmental risk factors and mental problems). In other words, the loadings of each variable reveal to what extent a single variable contributes to the maximal correlation relationship.

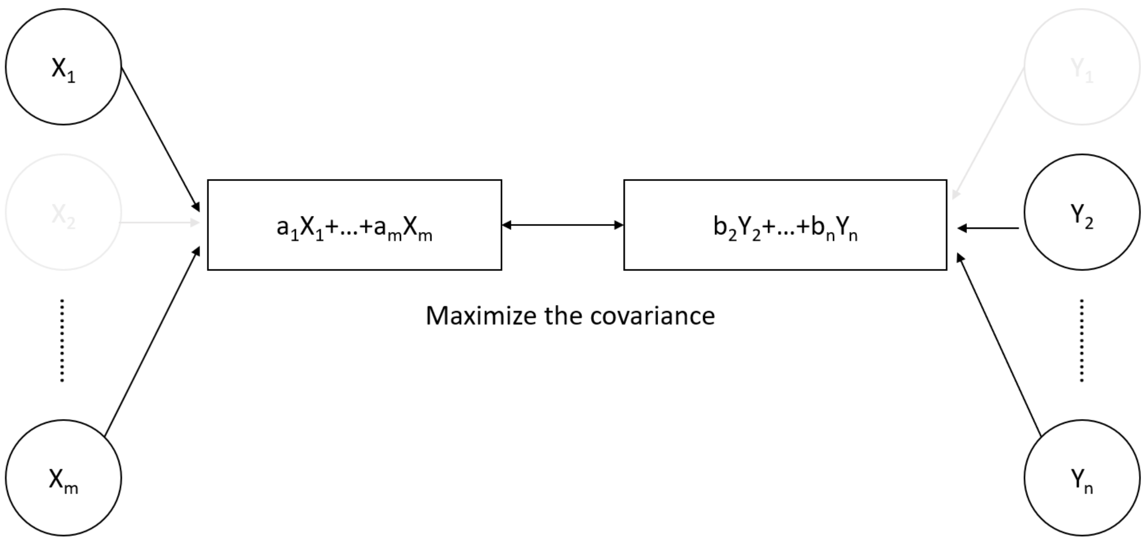
Figure 2.1



Note: Canonical correlation analysis (CCA) maximizes the correlation by maximizing the covariance. Every variable (X_1, X_2…X_m; Y_1, Y_2…Y_n) is loaded with weights (a_1, a_2…a_m; b_1,b_2…b_n) in this example.

Although CCA is powerful, the results can be hard to interpret because each variable is loaded with weights (e.g., X_1 is loaded with a_1), hence contributing to the association. It is particularly burdensome when a wide range of features is examined, and the intention is to distil the most important correlated features. In many cases, only a few variables are loaded with a large exact value (e.g., 0.5, -0.3), and other variables' loadings are close to zero (e.g., 0.0006, -00003), meaning that they contribute little to the maximization of the covariance. In order to enhance the interpretability, L_1 penalty is introduced to CCA, and negligible non-zero loadings are forced to take an exact zero value. **Figure 2.2** illustrates this scenario, where a_2 and b_1, loadings of X_2 and Y_1, are close to zero and are forced to adopt an exact zero value. This method is termed sparse canonical correlation analysis (sCCA)(Witten & Tibshirani, 2009). sCCA is used and implemented in the project pipeline described in **Chapter 4**.

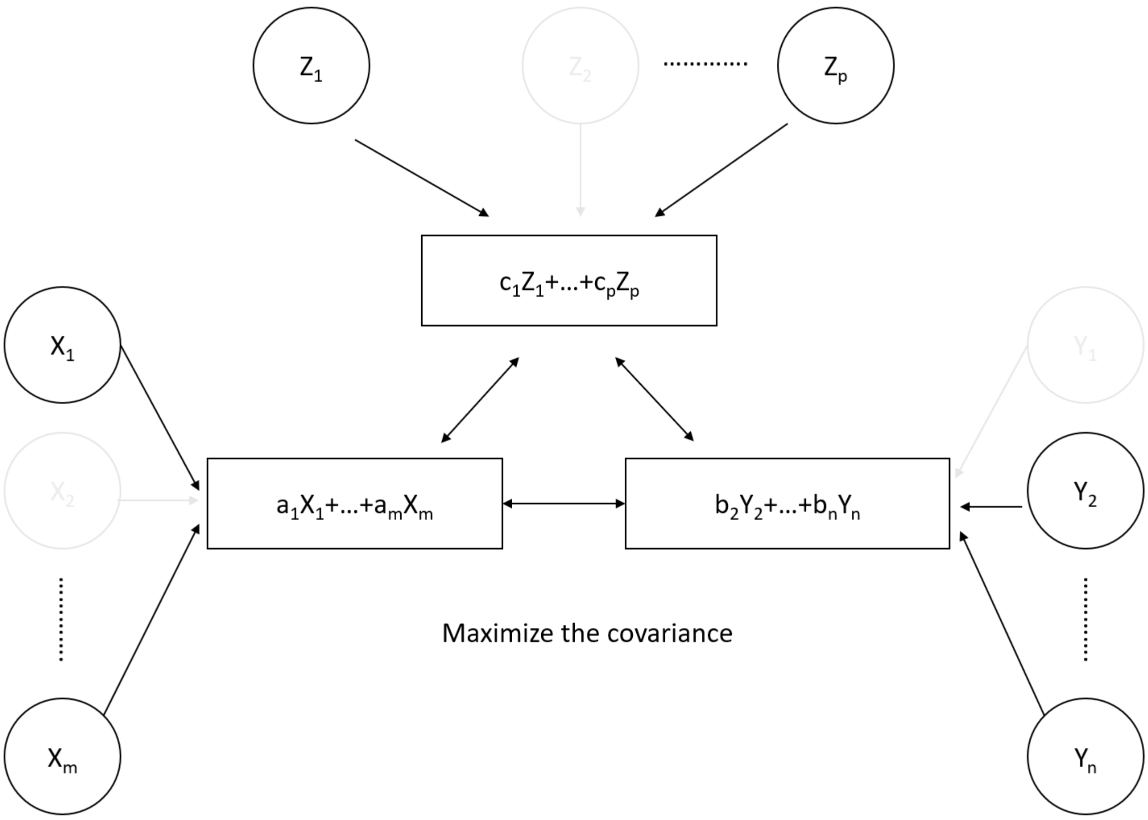
Figure 2.2



Note: Sparse canonical correlation analysis (sCCA) maximizes the correlation via maximizing the covariance and forces variables with loadings close to zero to take an exact zero. In this example, X_2's loading a_2 and Y_1's loading b_1 are close to zero and are forced to take an exact zero value by the sCCA algorithm. As a result, X_2 and Y_1 are eliminated.

sCCA can solve most problems where two views of data are involved. However, in this thesis, it is often that more than three views of data had to be examined simultaneously (e.g., satellite-detected nighttime light emission, ground-level urban features, mental problems). In order to achieve this, multiple sparse canonical correlation analysis (msCCA) is adopted since it can accommodate data with three or more views and improve interpretability by imposing sparsity on each data view (Ing et al., 2019)(**Figure 2.3**). msCCA is used and implemented in the project pipelines described in **Chapter 3** and **Chapter 4**.

Figure 2.3



Note: msCCA accommodates three and more views of data, maximizes the correlation via maximizing the covariance and forces variables with loadings close to zero to take an exact zero. In this example, X_2's loading a_2, Y_1's loading b_1 and Z_2's loading c_2 are close to zero and are forced to take an exact zero value by the msCCA algorithm. As a result, X_2 and Y_1 and Z_2 are eliminated,

However, a pitfall for CCA and its descendants is the issue of overfitting. Overfitting connotes the model created is too close to the limited data set. The model is valid only in the given dataset and can not be applied to other datasets. In other words, the created model is unable to generalize and can easily make inaccurate predictions in unrelated datasets.

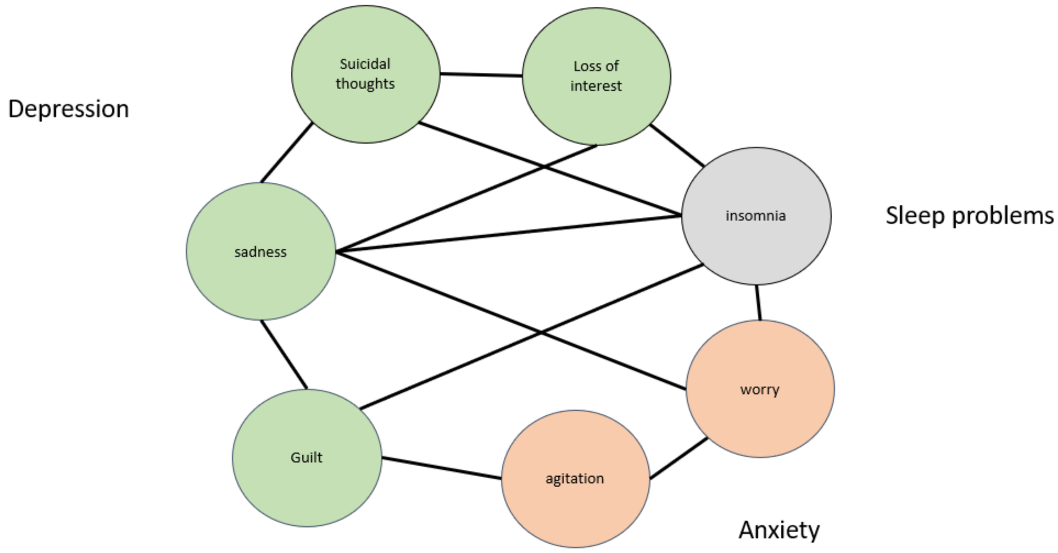
Since CCA aims at maximizing the covariance of the weighted sum, it is possible that the results are dataset-dependant and are not generalizable. In order to prevent this, all analyses involved in CCA (sCCA, msCCA) in this thesis were validated in an in-sample hold-out set.

2.3.2 Network analysis

2.3.2.1 Network analysis as psychopathology method

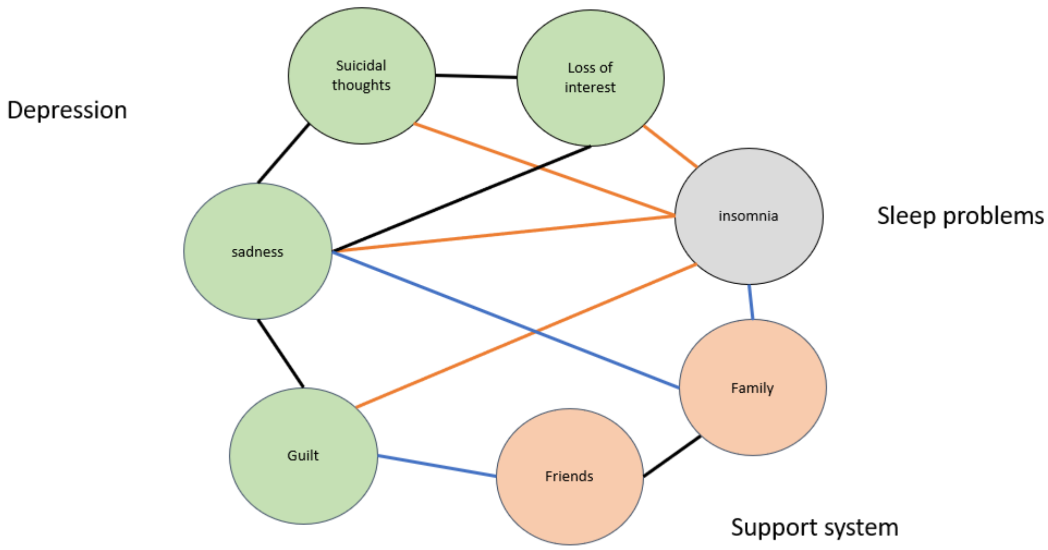
Network analysis is an analytical method based on graph theory to structurally examine relations among different elements (Cramer et al., 2010; Schmittmann et al., 2013; Scott, 1988). The elements are represented by *nodes* and their relations by *edges*. One of the most popular approaches is the Gaussian Graphical Model (GGM). In the GGM model, every edge between two nodes indicates a partial correlation, i.e., a relationship after controlling for all other nodes in the network. The role of a node in a network is assessed by a range of centrality statistics. Four centrality statistics are commonly used in the literature, including *closeness centrality*, *betweenness centrality*, *strength centrality* and *expected influence centrality*. Closeness centrality is based on the edge distance of one node to other nodes. Betweenness centrality assesses how many times does a node serve as the stepping stone on the shortest route between two other nodes. Of note, both strength centrality and expected influence centrality are based on the summed weights on edges connected to the node. Whereas the strength centrality sums the absolute value of the weights, expected influence centrality keeps the original sign of the weights before summing (Robinaugh et al., 2016). Strength and expected influence are more often used in psychopathology studies (Epskamp et al., 2018; Konac et al., 2021).

Figure 2.4



Note: Symptom network of depression, anxiety disorder and sleep problems.

Figure 2.5



Note: Environment-symptom network of depression, sleep problems, and support system. Orange edges represent the positive relationships between health problems and support system. Orange edges represent the negative relationships between health problems and support system (blue edges).

2.3.2.2 Bridge nodes

It should be noted that the strength centrality and expected influence centrality can be overestimated due to the clustering of nodes with similar concepts. For example, sadness and loss of interest are highly positively correlated to each other because they are related measures in depression (**Figure 2.4**). Due to their close connection, the strength centrality and expected influence can be high. But that does not imply that they both are highly correlated with other mental health problems and have an important influence on the whole network. On the other hand, if sadness and insomnia correlate, that might hint at the role of a transition between depression and sleep problems. Therefore, it is better to assess the centrality excluding edges between related symptoms (e.g., suicidal thoughts, sadness, loss of interest and guilt) within one mental health problem (e.g., depression), since that can overestimate the importance of the nodes. This concept is coined as *bridge centrality*, in which only the edges outside the predefined community (e.g., predefined mental health problem: depression, generalized anxiety disorder) are considered. In **Figure 2.4**, for example, the bridge centrality of sadness includes the relationship with insomnia and family but not the relationship with suicidal thoughts. The nodes with the highest bridge centralities serve as *bridge nodes* and are considered the symptoms bridging different mental health problems (Jones et al., 2021).

2.3.2.3 Beyond psychopathology. Network analysis on psychopathology-environment interaction

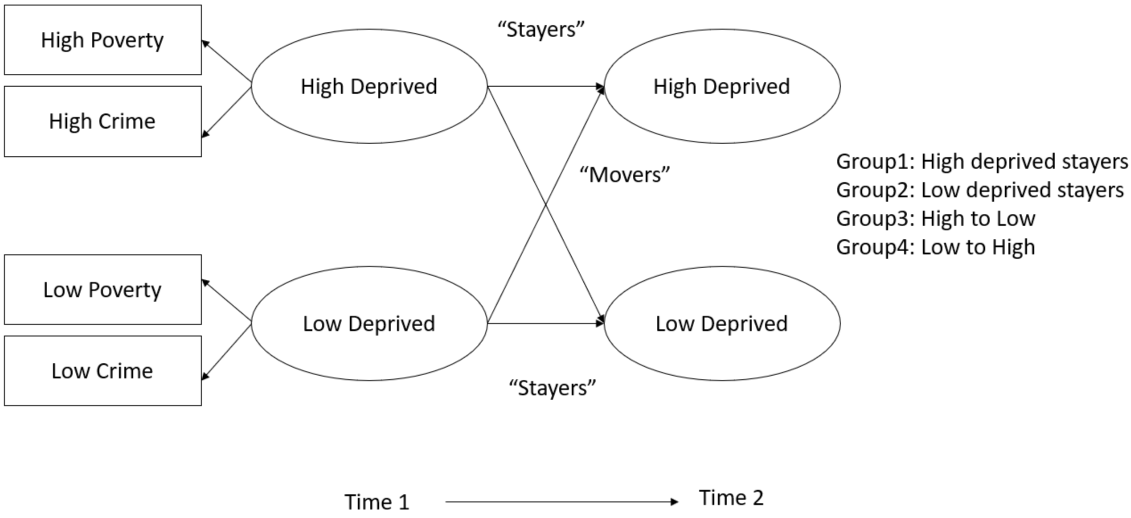
Although network analysis and bridge centrality are often used in psychopathology to identify bridge nodes (i.e., bridge symptoms) that link two different mental health problems, this concept can be theoretically extended to any kind of variables related to mental health. Few studies have used this approach for psychopathology-environmental interaction research

(Konac et al., 2021). In this thesis, network analysis is used as the tool to investigate the interactions between different layers of the Neighbourhood Mental Health Map. **Figure 2.5** illustrates a psychopathology-environment network in which the relationships between health problems and support systems are investigated. The relationships can be positively correlated (coloured in orange) or negative (coloured in blue). In this thesis, network analysis is used for investigating the mental-environmental interaction in **Chapter 3** and **Chapter 5**.

2.3.3 Latent transition analysis (LTA)

Latent variable analyses are a set of powerful tools in psychology, behaviour science and sociology. For example, participants among a population behave differently (e.g., consumer behaviour), and researchers aim to identify these groups. These groups are *latent classes* since they are not observable directly. By using latent class analysis (LCA), one can use latent categorical variables to characterise the groups, i.e., identify the latent classes, and categorize participants according to these latent classes. For example, in the example of consumer behaviour, consumers who prefer online shoping and only consume during seasonal sales can be one latent class. On the other hand, consumers who prefer in-store shopping and are not affected by the seasonal sales can be another latent class. However, when longitudinal data is available, researchers can further explore whether and how many per cent of the observed participants "move" to another latent class across time. This method is termed latent transition analysis (LTA, Graham et al., 1991).

Figure 2.6



Note: In this LTA example, participants in latent class "High Deprived" are exposed to neighbourhood-level observable characteristics "High Poverty" and "High Crime", and the participants in latent class "Low Deprived" are exposed to neighbourhood-level observable characteristics "Low Poverty" and "Low Crime". From Time 1 to Time 2, some participants remain in their original membership ("stayers"), whereas others changed to the other membership ("movers").

Figure 2.6 illustrates an LTA study. In this study, researchers want to know what are the features in the highly deprived neighbourhoods and low deprived neighbourhoods and whether participants have moved between neighbourhoods with different deprivation levels. Here, two latent classes, "High Deprived" and "Low Deprived" are identified. Participants who keep their original latent class membership from Time 1 to Time 2 (i.e., "High Deprived" → "High Deprived" and "Low Deprived" → "Low Deprived") are the "stayers". Participants who change from one latent membership to another from Time 1 to Time 2 are the "movers" (i.e., "High Deprived" → "Low Deprived" and "Low Deprived" → "High Deprived"). Therefore, in this two-latent class model, LTA categorizes the participants into four groups: two "stayers" and two "movers". Researchers can consequently investigate whether participants who change their exposure to deprivation behave differently than that who stay at the same level of deprivation. LTA is particularly useful in developmental psychology for two reasons. First, by identifying the “stayers” and the “movers”, researchers can identify the participants who indeed had chronic exposure to certain risk factors. Second, within the “movers”, researchers can further ask whether there is a critical time window for risk exposure in mental health problems.

Generally, the number of latent classes is suggested by the Akaike information criterion (AIC; Akaike, 1973), Bayesian information criterion (BIC; Schwarz, 1978) and sample-size-adjusted Bayesian information criterion (SABIC; Sclove, 1987). Although the objectives of AIC and BIC differ, lower AIC and BIC values indicate a better model fit (Nylund et al., 2007). However, one should not select a model solely based on these criteria but have to consider the conceptual appeal, scientific relevance and simplicity (Collins & Lanza, 2009, p.190; Ruppert et al., 2003, p.221). Entropy is used for ascertaining the accuracy of classification (Celeux & Soromenho, 1996). The closer the entropy is to one, the better the separation between latent classes. Conventionally, an entropy greater than 0.8 is considered a good separation (Clark & Muthén, 2009). In this thesis, LTA was used in **Chapter 5** to model the longitudinal deprivation patterns over time.

CHAPTER 3: Syndemic Associations between Nighttime Lights, Urban Features, Household Poverty, Depression Symptoms and Obesity

3.1 Abstract

3.1.1 Background

Nighttime light emission (NLE) is one of the most prominent urban features and has been found to be associated with decreased mental and physical health. However, NLE is intertwined with other urban environmental features, e.g., decreased air quality, lack of green space, which are also associated with decreased human mental and physical wellbeing. To date, no systematic exam, especially from a syndemic perspective, has been conducted regarding the interrelationship between NLE, other urban environmental features and mental, physical health.

3.1.2 Materials and methods

In this study, 200,393 UK Biobank Cohort participants with complete data were included. The study was conducted in two steps. First, the relationships between NLE, other urban environmental features (e.g., air pollution, green space) and mental and physical symptoms were assessed. Second, we evaluated the role of NLE in environment-symptom networks. Participants were stratified according to high or low NLE exposure. Then, Gaussian graphical model was applied to identify nodes that bridged urban environmental features and mental, physical symptoms. Finally, we compared the interconnectivity (i.e., global strength) of these environment-symptom networks in high vs low NLE.

3.1.3 Results

The findings showed that higher NLE was sydemically associated with higher urban features (e.g., higher air pollution, less green space, higher economic and neighbourhood deprivation), higher household poverty and diminished mental, physical wellbeings (e.g., higher depressed mood, higher tiredness/lethargy and obesity, $R_{training\_mean} = 0.2624$, $P_{training\_mean}<0.001$; $R_{test\_mean}=0.2619$, $P_{test\_mean}<0.001$). The global strength was significantly higher in the high NLE network than in the low NLE network (t=0.7896, $P<0.001$). In areas with high NLE, economic deprivation, household poverty and waist circumference linked the key urban features and mental health symptoms.

3.1.4 Conclusion

A syndemic interrelation between NLE, urban features, household poverty, and mental and physical symptoms has been identified. In areas with high NLE, urban environmental features are associated with mental and physical symptoms greater than in areas with low NLE.

Note: The findings presented in this study have been published under the title "*Nighttime lights, urban features, household poverty, depression, and obesity*", as an open access research article in *Current Psychology*, distributed under the terms of the Creative Commons CC BY license, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. The tables and figures presented in this chapter are created independently by Yi-An Liao and reused from the mentioned article under permission. Readers might find the similarities between the present chapter and the mentioned article, especially the method and result sections. It should be noted that Yi-An Liao performed all the analyses in this study and independently wrote the cited article.

3.2 Introduction

Urbanization is a prominent phenomenon worldwide, and more than 60% of the population will reside in urban areas by 2050 (Heilig, 2012). Moving to cities is often motivated by more career opportunities and better access to public and educational resources. However, this decision is also ensued by disadvantages, such as high living costs, exposure to more pollution and a stressful lifestyle. All these disadvantages experienced in urban areas can potentially lead to diminished wellbeing. Indeed, people living in urban areas have more mental health problems (Kovess-Masféty et al., 2005; March et al., 2008; Padhy et al., 2014; Purtle et al., 2019; Romans et al., 2011). For decades, urban designers and psychologists have been investigating the relationship between peoples' wellbeing and the living environment and promoting urban health.

3.2.1 Nighttime light emission and mental, physical health

One prominent urban feature that is also a potential risk factor for mental health problems is the artificial Nighttime Light Emission (NLE). Before the industrial revolution, exposure to nightlight was minimal. Moonlight from a full moon illuminates less than 1.0 lux, whereas a typical modern streetlight illuminates 15 lux (Bünning & Moser, 1969; Gaston et al., 2013). Since the 19th century, various types of lamps have been developed and been used for street illumination (e.g., Yablochkov candles in Paris, Zissis & Kitsinelis, 2009). A substantial body of studies has found a positive association between NLE exposure and insomnia and mood disorders (Min & Min, 2018; Paksarian et al., 2020). This association can be partially attributed to the impact of NLE on the circadian rhythm, which is not only an intrinsic mechanism but also needs external signals (i.e., light) to synchronize (Aschoff, 1965; Partch et al., 2014; Takahashi, 2015).

The key anatomical structure in charge of this biological and psychological synchronization is the suprachiasmatic nucleus (SCN). Suppose little light (i.e., in darkness) is sensed by the photosensitive retinal ganglion cells. In that case, this information is passed onto the SCN and then the pineal gland, which secretes melatonin, the critical endocrine regulator for circadian rhythm. Once exposed to melatonin, the peripheral cells enter into the “night mode”; in contrast, in the absence of melatonin, the peripheral cells enter into the “day mode” (Walker II et al., 2020). The secretion of melatonin is highly sensitive to light. A study illustrated that melatonin suppression in children is sensitive to dim light (5 to 10 lux)(Hartstein et al., 2022). Another study showed that, for sensitive individuals, as low as 10 lux already delayed the onset of melatonin secretion compared to < 1 lux (Phillips et al., 2019). Also, exposure to merely 5 lux amid sleep can already increase wake frequencies (Cho et al., 2016). Hence, it is not surprising that nighttime light emissions on the streets (5-15 lux) can already influence melatonin secretion and physiological outcomes (Keshet-Sitton et al., 2016; Walker II et al., 2020).

It has been observed that the melatonin concentration is lower in depression patients than in healthy participants (Khaleghipour et al., 2012). Indeed, the development of antidepressant Agomelatine, which targets both 5-HT_{2C} receptors and melatonin receptors (MT1/MT2), has encouraged further research on the antidepressive role of melatonin (Chenu et al., 2013; Satyanarayanan et al., 2018; Valdés-Tovar et al., 2018). However, melatonin is not the only hormone secreted rhythmically. Circadian rhythm also regulates insulin, glucocorticoid and other hormones (Albreiki et al., 2017; Kalsbeek et al., 2001; Son et al., 2011). Forming a negative feedback loop with the hypothalamic–pituitary–adrenal (HPA) axis, disturbed glucocorticoid is associated with depression (Dedovic & Ngiam, 2015).

Apart from the indirect pathways, the zeitgeber SCN also projects to emotion-related brain regions, e.g., the prefrontal cortex, which is plausible another pathway between NLE and mood disorders (Sylvester et al., 2002). Hence, it is biologically plausible that NLE can influence mood via indirect pathways (i.e., through the endocrine system) and direct pathways (i.e., through the neuroanatomic route). Indeed, studies have shown that NLE is associated with more severe anxiety, depressive symptoms, and even suicidal behaviours (Min & Min, 2018; Paksarian et al., 2020).

3.2.2 Other syndemic risk factors in the urban environment

Although studies have proposed the plausible pathways linking NLE and diminished mental health, it should be noted that NLE is not the single feature in urban areas. NLE often co-appears with other environmental risk factors that are also associated with diminished health. For example, air pollution (e.g., NO_2, $PM_{2.5}$) is often severe in places with higher NLE (Helbich et al., 2020). Fine particles can reach brain and lead to neuroinflammation (Calderón-Garcidueñas et al., 2008; Levesque et al., 2011). Yet, inflammation is one of the plausible mechanisms of depression (Troubat et al., 2021). It has been shown that air pollution, in particular the emission of fine particles, is correlated to increased common mental disorders (e.g., fatigue, sleep problems, irritability)(Bakolis et al., 2021).

Also, NLE co-occurs with less green space. For decades, green space has been regarded as attention-restorative and stress-relieving (Kaplan & Kaplan, 1989; Ulrich, 1983). Indeed, both lack of green spaces and reduced time spent in green spaces are positively associated with depression symptoms (van den Berg et al., 2017; Sarkar et al., 2018). Therefore, NLE is not only a risk factor for diminished mental health *per se*, but also a risk factor that clusters with other co-occurring risks that synergically contribute to various health problems. In other words, these co-occurring risk factors and health problems are *syndemics*.

3.2.3 Clustering of health problems in a set of risk features: a syndemic perspective

First introduced in the HIV studies, syndemic is defined as a "population-level clustering of social and health problems" (Mendenhall et al., 2017; Singer, 1996; Singer et al., 2017). However, this concept should be differentiated from *comorbidity*, which also describes the co-occurring health problems. Syndemic does not only emphasize the clustering of diseases but further illustrates the importance of *context* (e.g., social factors). According to the syndemic theory, certain contexts can create a specific condition where the clustering of diseases easily arises (Mendenhall et al., 2017).

It has been found that HIV patients had been exposed to a particular set of risk factors prior to infection, e.g., poverty (Wilson et al., 2014). People living in poverty have a higher propensity to engage in sex work and abuse substances (Adimora & Schoenbach, 2005; Marín, 2003). Higher exposure to these risks predisposes these individuals to the disease. The disease further traps HIV patients in this disadvantageous environment and leads to poor health conditions. It has been proposed that research on both communicable and non-communicable diseases should always consider the syndemic context.

Based on the syndemic perspective, certain urban environmental features can predispose the population at risk to mental and physical symptoms. These symptoms potentially further trap the population at risk in the areas with disadvantageous urban features.

3.2.4 Purpose of this chapter

Combining the syndemic theory and the Neighbourhood Mental Health Map framework (**1.1.3, Chapter 1**), the study presented in **Chapter 3** sought to identify the syndemic structure of mental and physical health problems embedded in the physical environment and social structure in the urban setting (**Figure 1.5**).

In more detail, in this project, we used a sparse multidimensional method to distil the syndemic associations between a prominent satellite-detectable urban physical feature (i.e.

Nighttime Light Emission), other urban physical features (e.g., air pollution, lack of green space), social structural constructs (e.g., economic and social deprivation) and individuals' mental and physical health. The first aim was to identify the syndemic structure (i.e., whether these variables simultaneously associate with each other). The second aim was to assess the magnitude of the syndemic connection between the key urban features and mental, physical health problems at the high versus low NLE level.

3.3 Materials and Methods

3.3.1 Analytical Sample

3.3.2 UK Biobank Project

The usage of the UK Biobank Project in **Chapter 3** was described in Liao et al. (2022). UK Biobank (UKBB) is a population-based cohort consisting of more than 500,000 adults who live in the United Kingdom. In this study, we used the data collected at baseline (2006-2010). Since previous studies have shown that characteristics of the circadian rhythm can be genetic-predisposed (Eastman et al., 2015; Egan et al., 2017; Malone et al., 2016), in order to minimize these confounding effects, we improved the homogeneity of ethnic background given by the participants (Liao et al., 2022). Therefore, we only included white participants residing at the same location in England for no less than three years. Participants were selected (n=200,393) if they had complete satellite-derived information, urban features, and individual wellbeing factors. UK Biobank received ethical approvals from the North West Multi-center Research Ethics Committee. The detailed scientific rationale and cohort protocol are described elsewhere (Sudlow et al., 2015).

3.3.3 Geo-position data acquisition

The geo-position data acquisition was described in Liao et al. (2022). The geo-position information for each participant is derived from the postcode linked with their home address, and was converted to east and north coordinates in the Ordnance Survey reference. For data protection reasons, the geo-position information was rounded to the nearest 1 kilometre and converted into geographic longitude and latitude for NLE data preparation.

3.3.4 NLE data acquisition

The acquisition of NLE data was described in Liao et al. (2022). NLE data was collected by DMSP/OLS (The Defense Meteorological Program/Operational Line-Scan System) NTL (Version 4) provided by the Earth Observation Group of the Payne Institute for Public Policy, Colorado School of Mines (Baugh et al., 2010; Elvidge et al., 1997), covering annual NLE from 1992 to 2013. OLS sensors are used to detect global cloud distribution and can also detect visible and near-infrared nighttime emissions related to human activity (e.g., city lights, gas flares) on the Earth’s surface (Croft, 1973). OLS data has been widely used in the literature. For instance, researchers have been using OLS data to monitor a range of human activities (e.g., settlements, population growth, and socioeconomic activity)(Huang et al., 2014; Small et al., 2005). Each OLS detects every location on Earth every 24 hours. It is important to note that the follow-on instrument for low-light imaging of Earth at night is the Visible Infrared Imaging Radiometer Suite (VIIRS) on board the Suomi National Polar-orbiting Partnership satellite (launched in 2011). The day/night band of VIIRS provides several key improvements over DMSP-OLS data, including a uniform Ground Instantaneous Field of View from nadir to edge of scan, a reduced pixel footprint, lower detection limits, larger dynamic range, in-flight calibration, and finer quantization (Elvidge et al., 2017). However, the VIIRS-DNB data is only available from 2012 onward, which does not coincide with the UK Biobank baseline period (namely, from 2006 to 2010). Thus, the present study relied on DMSP/OLS observations. DMSP/OLS data was extracted from Google Earth Engine (GEE) (https://earthengine.google.com/). Since the present study is dedicated to the relationship between long-term NLE exposure and mental, and physical wellbeing, the per-pixel mean value of NLE throughout the baseline period was computed (Liao et al., 2022).

3.3.5 Categories for urban features

As described in Liao et al. (2022), urban feature measures used in this study are based on participants' living addresses and are available from UKBUMP (Sarkar et al., 2015). 275 urban feature measures were selected, which encompassed different kinds of urban geographic measures (e.g., air pollution, sound pollution, accessibility to green spaces, indexes for economic deprivation, indexes for neighbourhood deprivation, accessibility to health care, factory, and public service). Here, similar variables were grouped into categories. For instance, "Nitrogen dioxide", "nitrogen oxides", "$PM_{2.5}$", and "PM_{10}" were grouped into the urban feature category: "air pollution". The grouped variables and their constituent measures are listed in **Table S3.1**. After z-normalisation of the measures, a principle component analysis was carried out in each category. Only the measures with loadings no less than 0.3 in the first component remained in further analysis. The first component was used as the score of each urban feature category.

3.3.6 Individual wellbeing factors

As described in Liao et al. (2022), there are three domains in the individual wellbeing factors: (1) mental wellbeing, (2) physical wellbeing and (3) economic wellbeing. In more detail, mental wellbeing included nine measures related to depression and anxiety symptoms. Physical wellbeing included four measures of obesity, three measures of physical activity and six measures related to sleep patterns. Economic wellbeing had one measure describing household poverty. All measures were based on the UKBB baseline. The description of individual wellbeing factors is presented in **Table S3.2**.

3.3.6.1 Depression and anxiety symptoms

As described in Liao et al. (2022), depression and anxiety symptoms were based on the Mental Health category in UKBB. Depression symptoms consisted of the frequency of the following symptoms in the last two weeks: depressed mood, unenthusiasm/disinterest, tenseness/restlessness, and tiredness/lethargy. Anxiety symptoms consisted of the following symptoms: irritability, nervous feelings, worrier/anxious feelings, tense/highly strung, and worry too long after embarrassment.

3.3.6.2 Obesity measures

As described in Liao et al. (2022), the obesity measures included four measures. They were: (1) body weight (Kg), (2) body mass index (Kg/m^2), (3) waist circumference, and (4) body fat percentage (bioelectric impedance). Waist circumference was measured under a standardized procedure with a measuring tape. During measurement, the participants stood upright and crossed their arms on the chest. Body fat percentage was measured by Tanita BC418MA body composition analyzer, between 1% and 75% in 0.1% increments.

3.3.6.3 Physical activity

As described in Liao et al. (2022), participants answered how many days in a week they performed physical activities in varying intensity: vigorous, moderate physical activity, or walking for more than ten minutes. UKBB described vigorous physical activity as activities that lead to sweating and hard breathing (e.g., heavy lifting). Moderate physical activity can be cycling at a normal speed.

3.3.6.4 Sleep pattern

As described in Liao et al. (2022), six measures related to sleep patterns or behaviours were included in this study. These measures are: whether the participants had difficulty in falling and maintaining sleep, had difficulty in getting up in the morning, took a nap, fell asleep without intention during the day, and received complaints about snoring from their partners. Participants were also asked for their sleep duration during 24 hours.

3.3.6.5 Household poverty

As described in Liao et al. (2022), the individual economic wellbeing was based on household poverty. In UKBB, participants were categorized into five categories based on their average annual household income before tax (less than £18,000, £18,000 to £29,999, £30,000 to £51,999, £52,000 to £100,000, and greater than £100,000). Here, we inversely coded the household income categories to represent the level of household poverty.

3.3.6.6 Population density

As Liao et al. (2022) described, the population density was based on the measure "Home area population density - urban or rural", based on the 2001 census from the Office of National Statistics. In UKBB, population density is categorized into five groups: Urban, Town and Fringe, Village, Hamlet, and Dwelling.

3.3.6.7 Covariates

As stated in Liao et al. (2022), NLE, categories for urban features and individual wellbeing factors were controlled for age, sex, and population density. Individual wellbeing factors were further controlled for assessment centres.

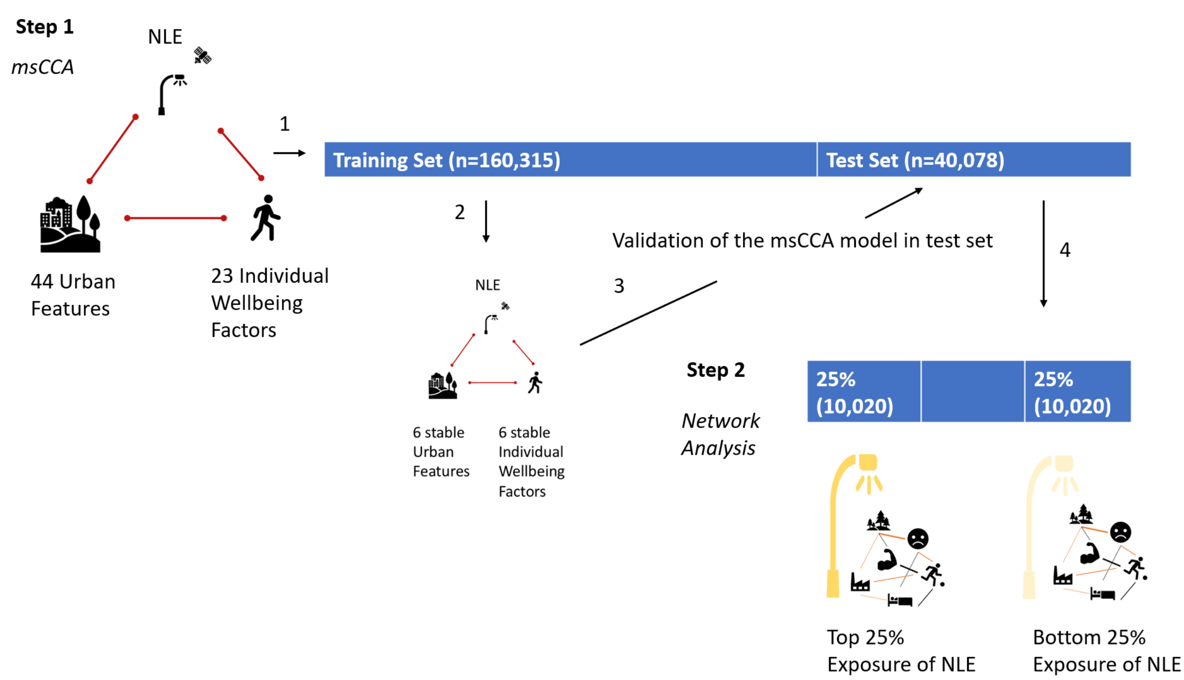
3.3.7 Statistical Methods

3.3.7.1 Step1. Using msCCA to identify the syndemic structure of NLE, urban features and individual wellbeing factors

In Step1, as described in Liao et al. (2022), we performed a multiple sparse canonical correlation analysis (msCCA) to identify the syndemic structure of NLE, urban features, and individual wellbeings. Canonical correlation analysis (CCA) is a widely used statistical method employed in psychology and other disciplines. The aim of CCA is to identify associations between two sets (often termed as “views”) of variables by maximising their covariance. Being a powerful tool, CCA may generate results which are difficult to interpret. In a typical CCA result, all variables (i.e., predictors) are loaded with non-zero, meaning that every predictor contributes to the association. Since this study aims to distil the syndemic structure in an urban neighbourhood, it is crucial to differentiate between the important and unimportant predictors. In order to improve interpretability, L_1 penalty is introduced to CCA, termed *sparse CCA* (sCCA)(Witten & Tibshirani, 2009). With L_1 penalty, the algorithm of sCCA still aims to maximise the covariance and forces the negligible non-zeros weights to take an exact zero value. Hence, the predictors with small non-zeros weights will be eliminated, facilitating the interpretation of the result.

Nevertheless, sCCA only accommodates two views of data. In the present study, we intended to identify the syndemic structure between three views of data (i.e., NLE, urban features and individual wellbeing); hence another algorithm is needed. Multiple sparse canonical correlation analysis (msCCA), designed as an extension of sCCA, is able to deal with more than two views of data while still improving the interpretability by imposing the sparsity (Ing et al., 2019; Tenenhaus et al., 2014). However, like CCA and sCCA, msCCA is vulnerable to overfitting, meaning that the model created can be only valid in the current dataset and may not be generalized. In order to overcome this disadvantage, we designed an in-sample validation with a hold-out test set to yield an unbiased estimate of model performance (**Figure 3.1**). Participants were randomly assigned to a training set (80%, n=160,315) and a test set (20%, n=40,078). We first tried to identify the stable urban feature categories and individual wellbeing factors. Here, we applied msCCA in the training set as a stability selection procedure with 50% subsampling and random sparsity. In a subsampling trial, the predictors (i.e., urban feature categories or individual wellbeing factors) that were not loaded with zero were recorded. Such a procedure was repeated 1,000 times. The stable urban features and individual wellbeing factors were the predictors appearing with non-zero weights in more than 75% of the stability selection subsampling trials (Meinshausen & Bühlmann, 2010). After identification of the stable urban features and individual wellbeing factors, msCCA was applied to these stable predictors in the training set without imposing any sparsity. Here, we ascertained the correlation coefficient of the training set and the weights of the stable urban feature categories and individual wellbeing factors. As a validation step, the weights obtained from the steps described above were applied to the test set, resulting in the correlation coefficient of the test set. We performed permutation tests (1,000 times) to ascertain the significance level. The permutation test was performed separately in the training and the test set. The analysis described in this section was carried out in Matlab (R2018b).

Figure 3.1



Note: Analytical pipeline. There are two steps in the analysis. Step1 consists of an in-sample validation msCCA, and Step 2 consists of network analysis. 1) msCCA was performed on NLE, 44 urban features and 23 individual wellbeing factors in the training set (n=160,315). 2) The stability selection procedure was performed in the training set with random sparsity 1,000 times. Here, we identified the stable predictors, i.e., six urban features and six individual wellbeing factors that had non-zero weights above 75% of the trials. These predictors were regarded as stable variables. Then, the correlations between NLE, six stable Urban Features and six stable Individual Wellbeing Factors were assessed. 3) In order to prevent overfitting, the model generated in the training set was validated in the test set (n=40,078). 4) The network analysis was performed in the test set. Participants exposed to the top 25% NLE and bottom 25% NLE in the test set were extracted for the network analysis. This step is to assess the difference between the environment-symptom network in high NLE and in low NLE. (figure reused and text adapted from Liao et al., 2022 CC BY 2.0)

3.3.7.2 Step2. Using network analysis to identify the variables bridging environment and mental-physical symptoms.

In Step2, as described in Liao et al. (2022), the interaction between the environment and mental-physical symptoms was assessed using network analysis. This was carried out for participants at high and low levels of NLE exposure. To avoid potential double-dipping, Step2 was only carried out using the test set (n=40,078). Participants who were exposed to the highest 25% (high NLE group, n=10,020) and the lowest 25% NLE (low NLE group, n=10,020) were selected for the following network analysis (**Figure 3.1**).

Network analysis is a multivariate analytic tool based on graph theories. The variables are depicted as "nodes" and their relationships as "edges". In order to assess the importance of nodes in a given network (i.e., centrality), previous studies have used different measures, including *strength*, *betweenness*, *closeness* and *expected influence*. However, variables measuring similar phenomena often have a strong relationship, hence high values in some centrality values (e.g., strength, expected influence). For example, both depressed mood and loss of interest are symptoms of depression and are often highly correlated. However, this strong relationship does not mean that it has a central role in the environment-symptom network. Therefore, in this study, we used the *bridge centrality*, meaning that we only took the relationship between environment and symptoms into account and ignored the relationships within the environment nodes or symptoms nodes.

In the network analysis, we regrouped the identified stable urban feature categories and individual wellbeing factors into two pre-defined communities: environment and mental-physical symptoms. The environment community included: air pollution, green space, economic deprivation, neighbourhood deprivation, distance to education, distance to public services, and household poverty. Mental-physical symptoms were: depressed mood, unenthusiasm/disinterest, tiredness/lethargy, waist circumference, and nap during day.

Gaussian Graphical Model (GGM) was estimated for each NLE group using the R package, *qgraph* (Epskamp et al., 2012). In a GGM network, every edge between two is a partial correlation, indicating a conditional independence association (Schellekens et al., 2020). In order to assess the importance of each node (i.e. centrality), the R package *networktools* was used to assess the 1-step bridge expected influence. The 1-step bridge expected influence is the sum of all edge weights linking a specific node in a given community, to nodes in other predefined communities (Jones et al., 2021; Opsahl et al., 2010; Robinaugh et al., 2016). Since the original signs of edge weights are kept, the 1-step bridge expected influence can be viewed as an indicator for network activation of one given node (Robinaugh et al., 2016). In Step2, nodes with the top 20% 1-step bridge expected influence were regarded as bridge nodes in the network. The bridge nodes are considered nodes linking two predefined communities and are central in the network activation. We ascertained the stability of the networks by a case-dropping bootstrapping (n boots = 1,000) with the R package *bootnet* (Epskamp et al., 2018). We also compared the two networks with different NLE exposures by performing the permutation-based Network Comparison Test (NCT) (van Borkulo et al., 2016). NCT assesses the difference in network structure and global strength. Global strength is defined as the absolute weighted sum of all the edges in a network. All network analysis described in this section was carried out in RStudio (R_Core_Team, 2013).

3.4 Results

3.4.1 Descriptive Statistics

The sample in the present study included 200,393 participants (49.51% male) from the UKBB cohort. Information of mean age, mean NLE exposure, information on qualifications, partnership, and household income are listed in **Table 3.1** (Liao et al., 2022).

Table 3.1. Demographics of the data sets

	Whole data	Training set	Test set	High NLE	Low NLE
Number	200,393	160,315	40,078	10,020	10,020
Sex (male) No.(%)	99,218(49.51)	79,294(49.46)	19,924(49.71)	5,217(52.07)	5,026(50.16)
Age (SD)	56.46(7.94)	56.47(7.93)	56.41(7.96)	57.69(7.53)	56.61(7.88)
Mean NLE(SD)	53.46(13.00)	53.48(13.00)	53.41(12.99)	59.79(7.03)	36.90(13.70)
Qualifications No.(%)					
College/University	69,983(34.92)	55,865(34.85)	14,118(35.23)	3,931(39.23)	3,566(35.59)
A level/AS levels	24,191(12.07)	19,350(12.07)	4,841(12.08)	1,074(10.72)	1,362(13.59)
O level/GCSEs	45,475(22.69)	36,433(22.73)	9,042(22.56)	1,927(19.23)	2,326(23.21)
CSEs	10,897(5.44)	8,712(5.43)	2,185(5.45)	453(4.52)	504(5.03)
NVQ/HND/HNC	13,480(6.73)	10,792(6.73)	2,688(6.71)	640(6.39)	675(6.74)
Other qualifications	9,999(4.99)	8,047(5.02)	1,952(4.87)	469(4.68)	513(5.12)
None of above	26,368(13.16)	21,116(13.17)	5,252(13.10)	1,526(15.23)	1,074(10.72)
Partnership No.(%)					
Living alone	29,050(14.50)	23,241(14.50)	5,809(14.49)	1,898(18.94)	1,128(11.26)
Living with a partner	158,665(79.18)	126,984(79.21)	31,681(79.05)	7,421(74.06)	8,366(83.49)
Household income No.(%)					
>£100,000	12,124(6.05)	9,647(6.02)	2,477(6.18)	858(8.56)	596(5.95)
£52,000 to £100,000	45,841(22.88)	36,747(22.92)	9,094(22.69)	2,105(21.01)	2,491(24.86)
£30,000 to £51,999	55,278(27.58)	44,071(27.49)	11,207(27.96)	2,511(25.06)	2,971(29.65)
£18,000 to £29,999	50,528(25.21)	40,436(25.22)	10,092(25.18)	2,478(24.73)	2,549(25.44)
< £18,000	36,622(18.28)	29,414(18.35)	7,208(17.98)	2,068(20.64)	1,413(14.10)

(table reused from Liao et al., 2022 CC BY 2.0)

3.4.2 Step1. Identification of syndemic structures of high NLE, detrimental key urban features and diminished individual wellbeing.

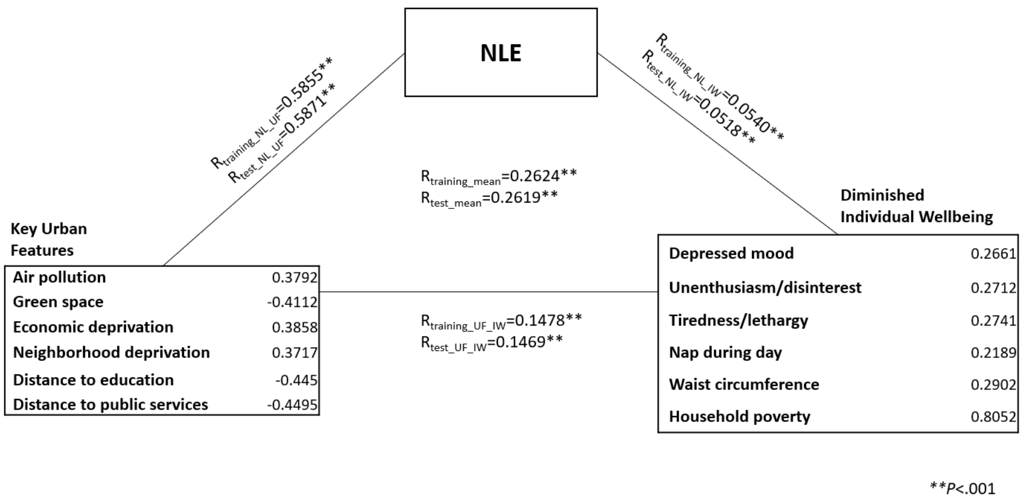
The findings from Step1, as shown in Liao et al. (2022), revealed that NLE is syndemic with key urban features and reduced individual wellbeing ($R_{training\_mean} = 0.2624$, $P_{training\_mean} < 0.001$; $R_{test\_mean} = 0.2619$, $P_{test\_mean} < 0.001$)(**Figure 3.2**).

In more detail, six of 44 urban feature categories were identified as key syndemic urban features: air pollution, lower green space, economic deprivation, neighbourhood deprivation, and shorter distance to education and public services. Among 23 individual wellbeing factors, six contributed to the syndemic structure. Of note, diminished economic wellbeing (i.e., household poverty) was the most prominent reduced individual wellbeing factor in the syndemic structure.

Factors related to diminished mental wellbeing included: depressed mood, unenthusiasm/disinterest, and tiredness/lethargy. Among the measures of obesity, only waist circumference contributed to the syndemic structure. One disturbed sleep pattern, nap during day, also contributed to the syndemic structure.

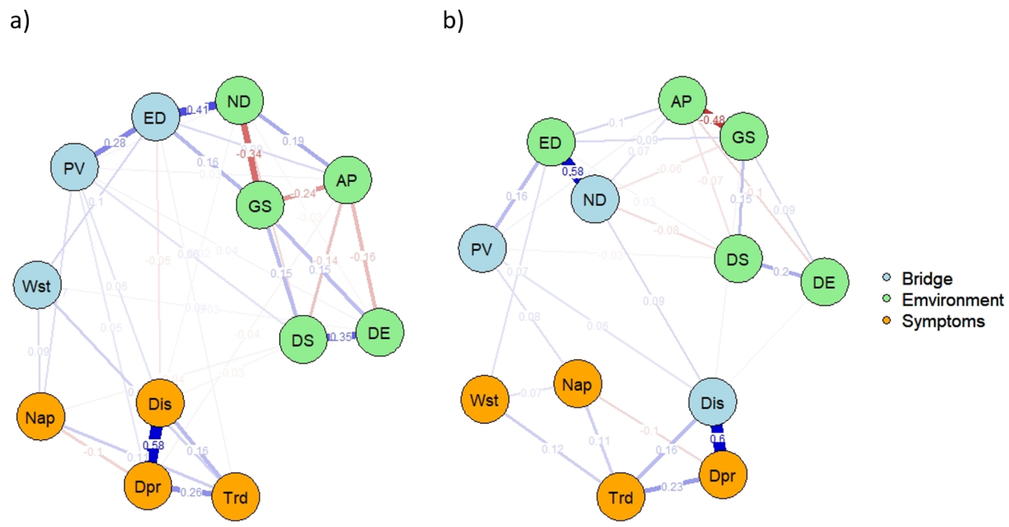
Although the overall msCCA correlation coefficient is significant ($R_{training\_mean} = 0.2624$, $P_{training\_mean} < 0.001$; $R_{test\_mean} = 0.2619$, $P_{test\_mean} < .0001$), it is possible that the overall relationship between these three views was driven by only one or two correlations. Hence, the relationships between each view pair were further examined. To ascertain the significance level, we performed a permutation test (1,000 times) in the training set and in the test set. As presented in Liao et al. (2022), the relationship between NLE and diminished individual wellbeing ($R_{training\_NL\_IW} = 0.0540$, $P_{training\_NL\_IW} < 0.001$; $R_{test\_NL\_IW} = 0.0518$, $P_{test\_NL\_IW} < .0001$), the relationship between between NLE and key urban features ($R_{training\_NL\_UF} = 0.5855$, $P_{training\_NL\_UF} < 0.001$, $R_{test\_NL\_UF} = 0.5871$, $P_{test\_NL\_UF} < 0.001$), and the relationship between key urban features and diminished individual wellbeing ($R_{training\_UF\_IW}$ =0.1478, $P_{training\_UF\_IW}$ <0.001; $R_{test\_UF\_IW}$ =0.1469, $P_{test\_UF\_IW}$ <0.001) were all significant in the training set and were validated in the test set.

Figure 3.2



Note: The syndemic relationships between NLE, key urban features and diminished individual wellbeing were identified. The values of $R_{training\_X1\_X2}$ and $R_{test\_X1\_X2}$ are the correlation coefficients between any pair of the data views, annotated with NL (*NL*E), UF (Key *U*rban *F*eatures) and IW (*I*ndividual *W*ellbeing). The means of these three correlation coefficients in the training and the training set are $R_{training\_mean}$ and R_{test_mean}. The significance was ascertained via permutation tests, performed in the training test and the test test, respectively. (Figure reused and text adapted from Liao et al., 2022 CC BY 2.0)

Figure 3.3



Note: High NLE (top 25% NLE, a) and low NLE (bottom 25%, b) environment-symptom networks. Dpr: frequency of depressed mood in the last two weeks; Dis: frequency of unenthusiasm/disinterest in the last two weeks; Trd: frequency of tiredness/lethargy in the last two weeks; Nap: Nap during day; Wst: Waist circumference; AP: Air pollution; GS: Green space; ED: Economic deprivation; ND: Neighborhood deprivation; DE: Distance to education; DS: Distance to public services; PV: Household poverty. (Liao et al., 2022 CC BY 2.0)

3.4.3 Step 2 Examination and comparison of syndemic interactions between environment and mental-physical symptoms at high and low levels of NLE

3.4.3.1 Bridge nodes

In Step 2, as explained in Liao et al. (2022), we aimed to examine and compare the syndemic interactions between the environment and mental-physical symptoms in areas of high NLE exposure and low NLE exposure. As shown in Liao et al. (2022), **Panel a** and **panel b** in **Figure 3.3** illustrated the top 25% NLE network (high NLE network), and the bottom 25% NLE network (low NLE network), respectively. Here, the syndemic interactions are characterised by the interconnectivity and the nodes bridging the environment and mental-physical symptoms. As for interconnectivity, the high NLE network had more edges than the low NLE network. Here, we performed the network comparison test and ascertained a significant difference in structure between high and low NLE networks (invariance test: t=0.2749, $P<0.001$). Also, the global strength (i.e., interconnectivity) was significantly greater in the high NLE network than in the low NLE network (t= 0.7896, $P<0.001$), which means that there was a higher interconnection among nodes in the high NLE network.

The nodes scoring top 20% on 1-step bridge expected influence were considered bridge nodes and labelled as "bridge", coloured in blue in the networks (**Figure 3.3**). Of interest, household poverty bridged environment and mental-physical symptoms in both high and low NLE networks. Other bridge nodes were also identified. On the one hand, in the high NLE network, economic deprivation and waist circumference served as bridge nodes between environment and mental-physical symptoms. On the other hand, in the low NLE network, neighbourhood deprivation and unenthusiasm/disinterest served as bridge nodes between environment and mental-physical symptoms.

The results presented in this section have been published under the title:

"*Nighttime lights, urban features, household poverty, depression, and obesity*" (Liao et al., 2022 CC BY 2.0) in *Current Psychology*. Yi-An Liao performed all analyses, interpreted the results and independently wrote the peer-reviewed article.

3.5 Discussion

The study presented in this chapter is one of the first studies to employ the syndemic theory in the NLE field. The first part of the study illustrated that key urban features, together with higher mental and physical health problems, are clustered in high NLE regions. In the second part, it has been found that the key urban features formed a more condensed network with mental, physical health problems in areas with high NLE vs low NLE. Also, we identified the bridge factors, i.e., the key syndemic environmental risk factors and key syndemic health problems that bridge the environment and health problems. Of interest, regardless of the NLE level, household poverty was the bridge factor linking environment and other health problems. In the high NLE areas, economic deprivation and waist circumference also bridged key urban features (e.g., neighbourhood deprivation) and mental health symptoms (e.g., disinterest, feeling depressed). On the other hand, in the low NLE areas, neighbourhood deprivation, and unenthusiasm/disinterest bridged the key urban features (e.g., economic deprivation) and mental health symptoms (e.g., disinterest, feeling depressed)

3.5.1 Syndemic clustering of depression, obesity, poverty in high NLE areas

The present study adds to the current understanding of urban mental health in two ways. First, the present study revealed the syndemics structure in the high NLE areas. The findings indicated that in areas with high NLE and other urban features (e.g., severe air pollution, lack of green spaces, more severe economic neighbourhood deprivation), depressive symptoms, obesity and household poverty are syndemics. This finding is aligned with previous studies, which revealed that exposure to high NLE is associated with more mental problems and obesity (Lai et al., 2020; Paksarian et al., 2020). Of interest, the pathways where light information passes down in the central nervous system are also involved in metabolism and mood regulation (Fernandez et al., 2018; Hattar et al., 2006; Kalsbeek et al., 2011).

Whereas NLE partially accounts for depression and obesity, these two conditions are also bidirectionally linked. Depression, obesity and diet-related disorders (e.g., diabetes) are intertwined under the impact of disturbed endocrine and immune system. For example, cortisol, secreted as a stress-responding hormone, induces insulin resistance (Sjöstrand & Eriksson, 2009). Long-term exposure to excessive cortisol or cortisol dysregulation (e.g., flattened diurnal cortisol curve) can lead to the accumulation of visceral fat (Chrousos & Kino, 2007; Joseph & Golden, 2017).

Visceral fat is characterised by an overload of adipose tissue, inducing an inflammatory process and enhancing the level of pro-inflammatory cytokines (e.g., IL-6 and TNFα), which are also increased in depression patients (Kwon & Pessin, 2013; Fan et al., 2017). Of note, IL-6 plays an important role in depression. For example, IL-6 concentration is higher in depressed patients than in healthy participants (Dowlati et al., 2010; Howren et al., 2009; Köhler et al., 2017). Also, a study showed that IL-6 overactivity is correlated with higher suicidality (Kappelmann et al., 2021). Although the underlying mechanism is still not clear, a study showed that IL-6 could directly control the serotonin transporter, which is crucial in serotonin reuptake (Kong et al., 2015). Rudolf et al. (2014) further observed that IL-6 is higher in patients with atypical depression (characterized by weight gain) but not in typical depression.

The present study validated the clustering of depression and obesity, in particular, the accumulation of visceral fat, measured by waist circumference. It further illustrated the geographic and socioeconomic context in which the clustering of health problems can easily arise. This finding aligns with the syndemic theory, which proposes that specific contexts make the populations more prone to develop health problems. In turn, the health problems could further trap the people in the deprived context (Mendenhall et al., 2017; Mustanski et al., 2007). For example, with a qualitative approach, Mendenhall & Jacobs (2012) indicated that depression and diabetes are often clustered in the context of poverty and food insecurity. Mendenhall (2012, p13) coined the observed clustering of problems among female Mexican immigrants in Chicago, VIDDA (i.e., violence, immigration, depression, diabetes, and abuse). Admittedly, a qualitative approach can provide an in-depth perspective and allow researchers to explore participants' life stories, which the quantitative approach often ignores. However, the syndemics theory still requires validatable empirical evidence to lay a firm foundation. The present study validated the qualitative observation with multidimensional statistical tools and provided an analytical framework for evaluating syndemics structure.

3.5.2 Higher urban-symptom interaction in high NLE areas

The second novel finding is related to the interaction property in syndemic theory. Here, using network analysis, we modelled and compared the environment-symptom interaction in high NLE and low NLE. In more detail, the interconnectivity between the key urban features and the mental and physical health symptoms is assessed with global strength. The present study revealed that the high NLE network has a higher global strength than the low NLE network.

Furthermore, we examed how the key urban features are connected with mental and physical health problems. In other words, we tried to identify the bridge nodes in high and low NLE areas. In high NLE areas, socioeconomic status at the individual and neighbourhood level (i.e., household poverty and neighbourhood economic deprivation) bridged other key urban features and mental health problems. Of note, waist circumference (i.e., an indicator for accumulated visceral fat) bridged the key urban features and mental health problems. This indicated that obesity does not only co-occur with depression but also serves as the stepping-stone symptom for other mental, physical symptoms in high NLE areas. In other words, environmental risk factors are linked to mental problems through obesity.

On the other hand, in low NLE areas, the identified bridge nodes between the key urban features and mental health problems were neighbourhood deprivation and disinterest. The neighbourhood deprivation can be physical (e.g., poor housing conditions) and social (e.g., high crime rates). A UK study has found that diminished Housing Benefits led to higher depressive symptoms for populations in poverty, suggesting a causal relationship between poor living conditions and mental health problems (Reeves et al., 2016).

Moreover, criminological studies have revealed that criminal offences are often clustered at a micro-geographic level, also termed criminal hot spots (Weisburd, 2015). Recent findings further illustrated that such areas are not exclusively hot spots for crimes but also for poverty and mental problems (e.g., depression, Weisburd & White, 2019). According to the authors, this relationship is multifaced. On the one hand, the population prone to mental health problems might be forced to live in disadvantageous areas (e.g., due to limited financial resources). On the other hand, disadvantageous areas also influence their mental health in a negative way (Weisburd & White, 2019).

The present study supports previous findings and illustrates that low NLE characterizes such areas.

3.5.3 Limitations

The findings in this study should be interpreted in light of numerous limitations. First, although the present study illustrated that NLE, urban features and mental, physical health problems are syndemic, the causality between them is still unclear (McIsaac et al., 2021). It is plausible that individuals with certain heritable traits might prefer to live in areas with certain features (e.g., high NLE). Second, due to the collection time range of the sample (2006-2010), it was not possible to employ the latest VIIRS-DNB dataset (since 2012), which has better linear resolution than DMSP/OLS dataset. Future studies on recent cohorts can utilise the VIIRS-DNB dataset as the source of NLE data (Elvidge et al., 2013). Third, this study does not model the change in urban features over time (e.g., change in NLE). In other words, it is unclear how urbanization is correlated with mental and physical health problems. Fourth, this present study is based on the UK Biobank cohort, and the findings might not reflect the situations in other countries, especially developing countries.

3.5.4 Conclusions

The study discussed in this chapter illustrates how NLE, urban features and mental, physical health are associated. First, depressed mood, lack of interest, tiredness, and obesity are syndemic in areas with high NLE and key urban features. Second, the interconnectivity between key urban features and mental, physical problems is higher in high NLE areas than in low NLE areas. Future studies should clarify the causality between NLE, urban features, and mental and physical health problems. The findings presented in this chapter have been published in *Current Psychology* (Liao et al., 2022 CC BY 2.0).

CHAPTER 4: Identification of satellite-derived physical signatures of mental problems

4.1 Abstract

4.1.1 Background

Mental health disorders are the result of a complex interplay between individual and environmental factors. However, to date, it is still unknown whether it is possible to identify physical signatures (i.e., specific geographic patterns) of mental health problems. This study aims at identifying signatures of the physical environment of depression, anxiety, smoking and alcohol drinking, by using satellite raw data in UK biobank and identifying structural brain features correlated to these mental health problems and corresponding physical signatures.

4.1.2 Materials and Methods

We examined the association between satellite raw data and different mental health symptoms for N=279,242 participants (272,337 for the exploratory set and 6,905 for the hold-out set) drawn from the baseline of UK Biobank. Geoposition data was acquired from UKBB as latitude and longitude, and the MODIS (Moderate Resolution Imaging Spectroradiometer) satellite raw data (18 bands) was extracted from Google Earth Engine. Sparse canonical correlation analysis (sCCA) was applied for the identification of physical signatures of each mental health variable. Multiple sparse canonical correlation analysis (msCCA) was used for the identification of the brain signatures correlated to mental health variables and their satellite-derived physical signatures. For interpretation of the satellite-derived physical signatures, ground-level data from the UK Biobank Urban Morphometric Platform (UKBUMP) was used.

4.1.3 Results

Physical signatures of depression, smoking, and overdrinking were identified in the exploratory dataset (depression: R_{exp}=0.0551 P_{exp}<0.001; smoking: R_{exp}=0.0614 P_{exp}<0.001; overdrinking: R_{exp}=0.0354 P_{exp}<0.001) and validated in the hold-out set (depression: $R_{holdout}$=0.0395 $P_{holdout}$=0.003; smoking: $R_{holdout}$=0.05 $P_{holdout}$<0.001; overdrinking: $R_{holdout}$=0.0492 $P_{holdout}$<0.001). The satellite-derived physical signatures of depression and smoking are associated with urban features, such as being positively correlated to air pollution, density of streets and negatively correlated to greenspace, distance to education, distance to healthcare and distance to services (depression: $R_{training}$ = 0.6298 $P_{training}$ <0.001, R_{test} = 0.6135 P_{test} <0.001; smoking: $R_{training}$= 0.6987 $P_{training}$<0.001, R_{test}= 0.6975 P_{test}<0.001). The satellite-derived physical signature of overdrinking is associated more to suburban features, positively correlated to water density and negatively associated with air pollution (overdrinking: $R_{training}$= 0.3543 $P_{training}$<0.001, R_{test}= 0.3076 P_{test}<0.001). Depression and smoking behaviour and their satellite-derived physical signatures are correlated to reduced GMV (grey matter volume) of posterior regions of cerebellum. Overdrinking and its satellite-derived physical signature are associated with reduced GMV of the brain stem, right cuneal cortex, right lateral occipital cortex, left occipital pole, right planum polare, left precuneous cortex, left putamen, left and right thalamus and the overall volume of left and right thalamus.

4.1.4 Conclusion

By using satellite raw data, physical signatures of depression, smoking behaviour, and overdrinking behaviour were identified. Findings suggested that satellite-derived physical signatures of depression and smoking share an urban feature, whereas overdrinking satellite signature shows a suburban environment. Moreover, the brain features correlated to the meantal health measures and their corresponding satellite-derived physical signatures were identified. The current study showed the noval application of satellite raw data in mental health. Satellite raw data allows us to understand the topography of a specific mental disease at a global scale, and help decision-makers allocate resources to the potential risk zones with more efficiency.

4.2 Introduction

Mental health problems are major health burdens worldwide (Vos et al., 2015). According to estimation, mental health problems more than 10.0% of disability-adjusted life-years can be explained by mental health problems and by 2030, depression will be the first disability cause globally (Vigo et al., 2016; WHO, 2011).

4.2.1 Previous studies on the physical environment and mental health problems

Whereas individual risk factors for mental health problems have been intensively researched, studies on environmental influence on mental health mainly focused on psychosocial environments such as early trauma experience, sex abuse, and parenting style. Although less emphasis has been placed on investigating the relationship between the physical environment and mental health, there are intriguing findings showing, for example, an increased incidence of psychosis in urban settings (Faris & Dunham, 1939; March et al., 2008; Padhy et al., 2014). Other studies have found associations between mood disorders and living in urban areas (Kovess-Masféty et al., 2005; Purtle et al., 2019; Romans et al., 2011). Other studies also investigated the relationship between substance use (e.g., smoking and alcohol intake behaviour) and urbanicity (Dixon & Chartier, 2016; Donath et al., 2011; Grant, 1997; Völzke et al., 2006).

However, in the literature, most studies used census-level population density to define urbanicity and used ground-level data (i.e., geographic data collected and recorded by an administrative authority) to describe the urban physical environment (Melis et al., 2015). Although ground-level data (e.g., road density) can provide precise information, they suffer from administrative and temporal limitations. For example, measurements for attaining ground-level data might be different in each country. In order to overcome this drawback, a constant and continual longitudinal measurement of the standardised physical environment across various countries is warranted. Remote sensing using satellite data has been recording the change in the earth's surface for decades. It has witnessed an unprecedented change in the ecosystem and demographics throughout human history. The remote sensing technique constantly records the reflectance of light bands from the earth's surface. Geographers used the combination of these reflected light bands to construct a range of indexes. For example, Normalised Difference Vegetation Index (NDVI), an index estimating green coverage on the earth's surface, consists of a near-infrared light band and a visible red light band (Rouse, 1973). Another index, e.g., Normalised Difference Built-Up Index (NDBI), estimates the built-up area and consists of a short wave infrared band and a near-infrared band (Zha et al., 2003).

The usage of satellite-derived indexes overcomes administrative and temporal limitations and has been applied in mental health research. For example, NDVI was used to identify the protective association between residential greenness and depression (Song et al., 2019). Other authors might also develop their satellite index. For example, Xu et al. (2022) developed a satellite index summarising urbanicity and found a positive correlation between urban residence and depressive symptoms.

Nevertheless, the usage of satellite-derived indexes still limits the scope of research as to that of the ground-level data. For example, NDVI and NDBI are specific indexes designed to assess green spaces and built-up surfaces. Researchers using these indexes can merely establish the relationship between green spaces, built-up surfaces and mental health problems. In other words, researchers might have ignored other physical risk features because only a limited number of satellite-derived indexes are available. A novel methodology is warranted to systematically examine the relationship between the physical environment and mental health and identify *physical signatures* of mental health problems. Here, a physical signature refers to a specific geographic pattern in which a specific mental health problem is most likely to occur.

4.2.2 Usage of satellite raw data as a solution

Satellite raw data can be the solution and helps us with the identification of the physical signatures of mental health problems. In contrast to the satellite indexes derived from certain light bands (e.g., infrared and red light for NDVI), the satellite raw data refers to the original reflectance bands detected by the satellite. For example, Moderate Resolution Imaging Spectroradiometer (MODIS) continuously records 36 light bands of reflection from the earth's surface. Among these wavelength bands, 18 bands are typically used in remote sensing studies. The complete range of light bands, presumably, captures the most comprehensive to date geographical information for any earth's surface. With appropriate statistical tools, the usage of satellite raw data allows us to distil the physical signatures of different mental health problems (e.g., depression, anxiety, smoking and overdrinking).

4.2.3 Physical environment and brain

The human brain keeps receiving stimuli from the outer world and adapting to it. An increasing body of evidence shows the correlation between the physical environment (e.g., urbanicity, low green space, high air pollution) and changes in brain structure. For example, exposure to the urban environment at an early age is associated with a smaller right dorsolateral prefrontal cortex (Haddad et al., 2015). Another study also illustrated that participants exposed to urban exposure at a young age had reduced thickness in cortices of left dorsolateral prefrontal, medial prefrontal, and temporal regions (Besteher et al., 2017). Xu et al. (2022), using data from China and Europe, demonstrated that exposure in areas with high population density was correlated with smaller medial prefrontal cortex volume and larger cerebellar vermis volume. The relationship between other physical environmental characteristics (e.g., green spaces, air pollution) has also been reported. For example, long-term green spaces exposures were correlated with thicker grey matter in the prefrontal cortex and left premotor cortex (Dadvand et al., 2018). As for air pollution, a pervasive phenomenon in urban environments, Wilker et al. (2015) demonstrated that long-term exposure to $PM_{2.5}$ was correlated with reduced overall brain volume.

4.2.4 Purpose of this chapter

As stated, previous studies suggested some physical environment features (e.g., lack of green spaces) as risk factors for mental health (Song et al., 2019; Xu et al., 2022). However, to date, no studies have been using a systematic way to examine the relationship between the physical environment and mental health problems. The purposes of **Chapter 4** are threefold. First, we aimed to develop a systematic and comprehensive methodological pipeline to examine the relationship between the physical environment and mental health problems. Here, we used the satellite raw data derived from MODIS because it has the comprehensiveness of geographic information of a specific area (e.g., participants' neighbourhood). In more detail, by using the satellite raw data, we aimed to identify the satellite-derived physical signatures of depression, anxiety, smoking behaviour and alcohol intake behaviour in a large UK-wide cohort, UK Biobank.

Second, we aimed to prove the usability of the satellite raw data. That is, by using the available ground-level geographic data, we sought to interpret the identified satellite-derived physical signatures, which can be hard to interpret at first glance.

Third, we aimed at predicting the brain structure of mental problems and their corresponding physical signatures. This step allows us to assess the associations between the mental health, physical environment, and brain structure.

4.3 Materials and Methods

4.3.1 Analytical Sample

UK Biobank (UKBB) is a nationwide cohort including more than 500,000 participants (5.5% response rate) who reside in the UK. The baseline information, including questionnaires, interviews, and physical measurements, was collected between 2006 and 2010 across 21 collection centres in the UK. The geo-position of the participants and the mental problems measures collected at baseline were used in this study. To ensure some homogeneity of ethnic background and minimise the heritable preference for residential locations, only white subjects who have been living at the same home location in England for at least three years were included for further analysis (Cronqvist et al., 2014). Participants who did not complete all the mental health-related questions and did not provide geo-position information were excluded from the study. Based on these criteria, a total of 279,242 participants were included for further analysis. Based on the availability of the brain image data, the whole dataset was divided into an exploratory set (n=272,337, without brain image data) and a holdout set (n=6,905, with brain image data collected in Instance 2).

UK Biobank received ethical approvals from the North West Multi-centre Research Ethics Committee, the Community Health Index Advisory Group, the Patient Information Advisory Group, and the National Health Service National Research Ethics Service. The detailed cohort protocol, scientific rationale, and study design are described elsewhere (Sudlow et al., 2015).

4.3.2 Measurement of mental problems

4.3.2.1 Depression sum score

The depression sum score was computed based on four depression-related questions in the category ‘mental health’ in baseline, including (1) frequency of depressed mood in last two weeks, (2) frequency of unenthusiasm/disinterest in last two weeks, (3) frequency of tenseness/restlessness in last two weeks and (4) frequency of tiredness/lethargy in last two weeks (**Table S4.1**).

4.3.2.2 Anxiety sum score

The anxiety sum score was computed based on six anxiety-related questions in the category 'mental health' in baseline, which includes: (1) irritability, (2) nervous feelings, (3) worrier / anxious feelings, (4) tense / 'highly strung', (5) worry too long after embarrassment and (6) suffering from 'nerves' (**Table S4.2**).

4.3.2.3 Smoking

Current tobacco smoking status was based on the question: "do you smoke tobacco now?"

4.3.2.4 Alcohol Intake Amount

In the UKBB, participants provided information about their drinking frequency, monthly drinking behaviour and weekly drinking behaviour by types of alcohol. Five types of alcoholic beverages are included in UKBB questionnaires: red wine, white wine, beer, spirit and fortified wine. Participants answering the overall drinking frequency with "never" and "special occasions only" were considered as non-regular consumers of alcohol, hence imputed with zero. For participants who did not answer weekly intake frequency for a specific type but answered monthly for a specific type, the amount of each alcohol beverage was based on the monthly intake divided by four (weeks).

According to National Health Service in the UK, a regular glass of red wine and white wine contains 2.1 units of alcohol. A pint of beer contains 2.5 units, and a regular measure of spirit contains 1 unit. Fortified wine is considered as spirit, containing 1 unit. The total alcohol unit intake amount for one week was computed based on the frequency of weekly intake and the average unit of alcohol for each type of alcohol.

Participants who provided overall alcohol intake frequency information but did not provide the information for each specific type of alcohol were imputed by the frequency of alcohol intake and the mean of the five types of alcohol: 1.74 units ((2.1+2.1+2.5+1+1)/5).

4.3.2.5 Excessive alcohol intake (overdrinking)

Males and females who have more than 14 units of alcohol weekly were considered overdrinking (UK Chief Medical Officers' Alcohol Guidelines Review, 2016).

4.3.3 Geoposition data acquisition

Geoposition data of each participant was acquired from UKBB and converted to latitude and longitude.

4.3.4 Remote sensing satellite data acquisition

Google earth engine (GEE) is a platform providing satellite imagery and geospatial datasets with planetary-scale analysis for scientists. (https://earthengine.google.com/). In total, The Moderate Resolution Imaging Spectroradiometer (MODIS) consists of 36 bands. The most useful 18 bands are available at GEE and were included in this study. The remaining 18 bands (covering 0.9-14.4 um) are not available at GEE and are mostly employed for ocean and atmosphere research. The resolution of the extracted data was one km, and the period was from 2006 to 2010, covering the baseline period of UKBB. The mean value of each band throughout five years was computed for analysis.

4.3.5 Neuroimaging data

In the latest release, scanners are standard Siemens Skyra 3T running VD13A SP4 (as of October 2015), with a standard Siemens 32-channel RF receive head coil. All released data is from a single scanner for UK Biobank imaging in Cheadle Manchester. The T1 scanning protocol and details are as follows. The resolution is 1x1x1 mm. Field-of-view is 208x256x256 matrix. Duration is 5 minutes. Other information includes 3D MPRAGE, sagittal, in-plane acceleration iPAT=2, and prescan-normalise. It should be noted that UK BioBank started to collect neuroimaging data from Instance 2 (2014). More details are available in the official document for neuroimaging measurement of the UK BioBank (Stephen et al., 2020).

4.3.6 Neighbourhood Geographic Category

Measures derived from participants' living addresses and available from the resource UKBUMP (Sarkar et al., 2015) were employed to assess neighbourhood geographic features. A set of 275 neighbourhood geographic measures was selected, including air and sound pollution, greenspace availability, socioeconomic deprivation, land use density and slope.

Given that various measures examined similar aspects of the neighbourhood geography, PCA was employed to summarise the neighbourhood geographic measures into a smaller set of categories, thereby reducing the amount of measures used for subsequent analyses.

A set of 44 categories of geographic measures was defined based on the different aspects of the neighbourhood geography that were examined. In the case of the categories of distance and density to facilities, the generation of the categories was also guided by codes provided by UK Biobank, based on Address Base Premium land use classification codes and descriptions. After normalising the individual geographic measures, a principal component analysis (PCA) was carried out for each category. Only variables that had a positive loading of at least 0.3 in the first component were retained, and the scores from the first component were used as summary scores for each category. This allowed obtaining a single measure for each category of neighbourhood geographic features.

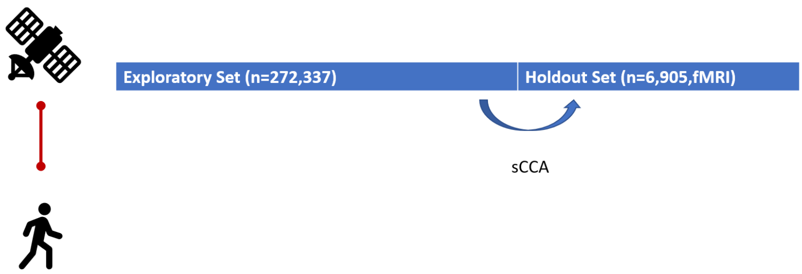
4.3.7 Covariates

Age, collecting sites and sex were controlled as covariates in the statistical analysis. For ROI analysis, a T1-based "headsize scaling factor" was used to correct subjects' head size (as suggested in the UK Biobank Imaging Documentation).

4.3.8 Statistical Analysis

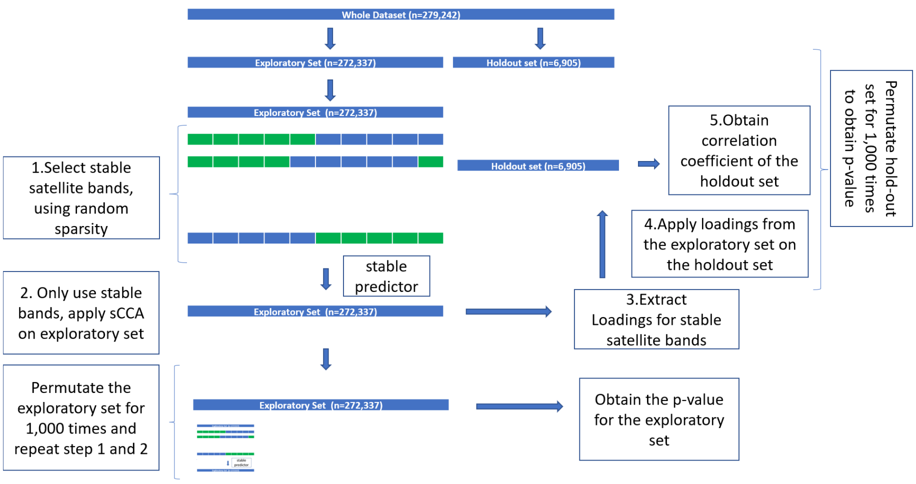
4.3.8.1 Step 1. Identification of satellite-derived physical signature of mental problems

Figure 4.1



Note: The whole sample was split into an exploratory set and a holdout set. The sCCA correlations between satellite-derived physical signatures and mental problems were assessed in the exploratory set and validated in the holdout set.

Figure 4.2



Note: The analytic pipeline for identifying satellite-derived physical signatures of specific mental problems.

Canonical correlation analysis (CCA) is a statistical method used to measure the linear association between two views of variables. CCA aims at achieving the maximum of the correlation by maximising the covariance of the weighted sum of each set. Although CCA is powerful, the results can be hard to interpret since each predictor is loaded. In order to enhance the interpretability, L_1 penalty is introduced to CCA, and negligible non-zeros loadings are forced to take an exact zero value. This method is termed sparse canonical correlation analysis (sCCA, Witten & Tibshirani, 2009). In Step 1, sCCA was used to select the satellite bands which construct the physical signature for each mental problem.

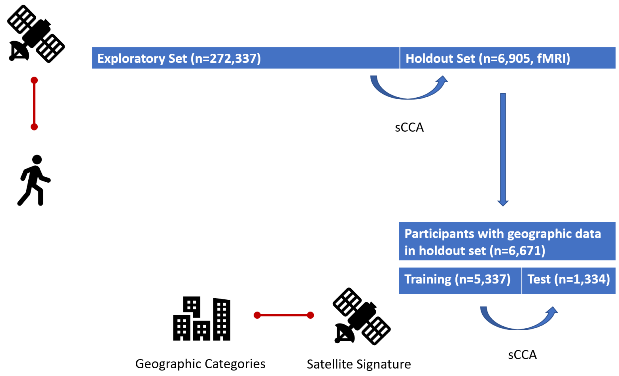
Before applying sCCA, all the behaviour variables and the satellite raw data were adjusted for age, sex and collecting sites. In order to prevent overfitting, an in-sample holdout design was used in this study. Since most of the participants in this study did not complete the MRI measurement, participants without MRI measurement data were allocated to the exploratory set (n=272,337). The participants with MRI measurements were grouped into the holdout set (n=6,905)(**Figure 4.1**). In order to determine the stable satellite predictors, a subsampling method was carried out in the exploratory set. Each time, 50% of the exploratory set was drawn, and the sCCA was run on the selected sample with a random sparsity between 0.1 to 1 imposing on the satellite view. The satellite bands with non-zero loadings were recorded (**Figure 4.2, box 1**). As for the stability check, the same procedure was repeated 100 times and the satellite bands appearing as non-zero loaded above 75% were considered stable (Meinshausen & Bühlmann, 2010)(**Figure 4.2, box 2**).

Then, sCCA was applied to the whole exploratory dataset using the selected stable bands without imposing any sparsity. This step is for ascertaining the correlation coefficient value and the loadings of the stable satellite bands (**Figure 4.2, box 3**). A permutation test was conducted to determine the significance level for the exploratory set. In each permutation trial, the order of the participants of one view in the exploratory set was randomly ordered, creating rotated data. The idea is: if there is a true correlation between these two views in the exploratory set, this rotation will destroy the relationship. Hence, sCCA would result in a low correlation coefficient (**Figure 4.2, box 4 and 5**). The same procedure described above, including the stability check, was applied to this rotated data, and the correlation coefficient was recorded. The permutation was conducted 1,000 times, and the p-value was determined as the number of permutation trials that had a higher correlation coefficient than the one from the non-rotated exploratory set, divided by the number of permutation trials.

For validation, the loadings identified in the exploratory set were tested in the holdout set to ascertain the correlation coefficient of the holdout set. A permutation test was conducted to determine the significance level for the holdout set. In each permutation trial, the order of the participants of one view in the holdout set was randomly ordered, creating a rotated holdout set. The loadings gained from the exploratory set were applied to the rotated holdout set, resulting in a correlation coefficient. The idea is: if the model generated from the exploratory set is also true for the holdout set, this rotation will destroy the relationship within the holdout set. Hence, the model would result in a low correlation coefficient in the rotated holdout set. The permutation was conducted 1,000 times, and the p-value was determined as the number of permutation trials that had a higher correlation coefficient than the one from the non-rotated holdout set, divided by the number of permutation trials.

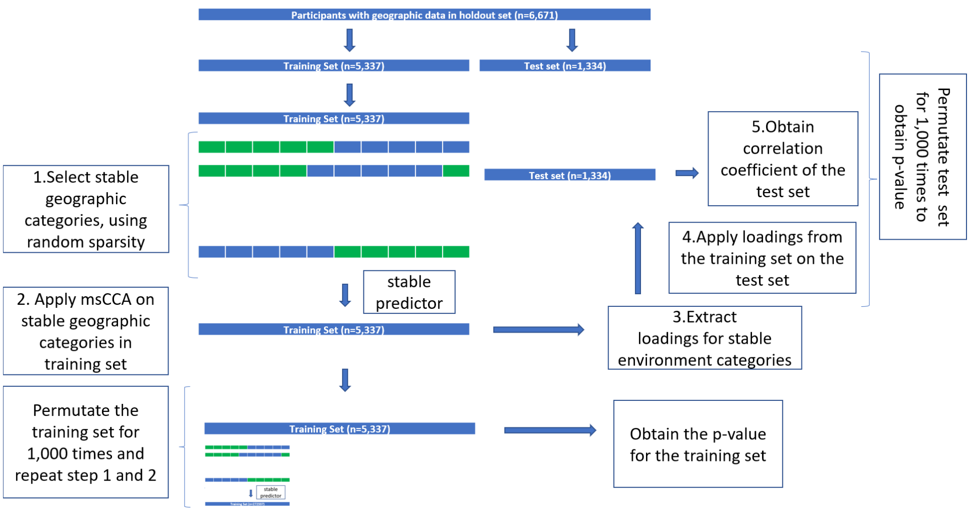
4.3.8.2 Step 2. Interpretation of the identified satellite-derived physical signatures

Figure 4.3



Note: The interpretation of the identified satellite-derived physical signatures was conducted within the holdout set. The holdout set was further divided into a training and a test set. The sCCA correlations between geographic categories and satellite-derived signatures were assessed in the training set and validated in the test set.

Figure 4.4



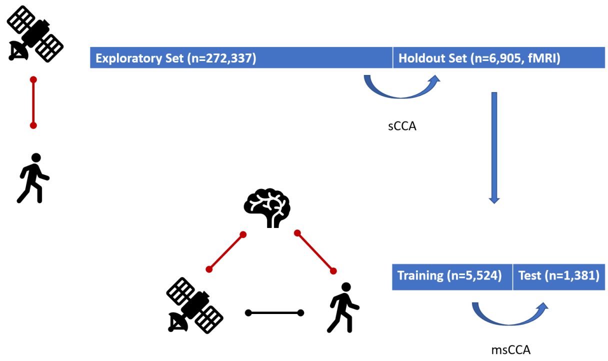
Note: The analytic pipeline for interpretation of the identified satellite-derived physical signatures

To interpret the satellite-derived physical signatures, the ground-level geographic data from UKBB was used. The ground level data was summarised by PCA into 44 geographic categories.

To prevent double-dipping, Step 2 was conducted on participants with geographic data information in the holdout set (**Figure 4.3**). After excluding the participants without geographic data, the new holdout set (n=6,671) was further randomly divided into a training set (80%, n=5,337) and a test set (20%, n=1,334). In the training set, sCCA was run on 44 geographic categories against each identified satellite-derived physical signature. A sub-sampling procedure was conducted for stability check. In each sub-sampling, 50 % of the new holdout set was drawn and sCCA with random sparsity from 0.1 to 1 was applied. The same procedure was repeated 100 times, and the non-zero loaded categories in each trial were recorded. Only the geographic categories appearing with non-zero loadings above 75 % of the trials were considered stable. For ascertaining the loadings and the correlation coefficient, sCCA was run on these stable geographic categories against the identified satellite-derived physical signature without imposing any sparsity. The loadings from the training set were applied to the test set for validation. The significance level of the results from the training set and the test set was ascertained by the permutation test. The pipeline is presented in **Figure 4.4**.

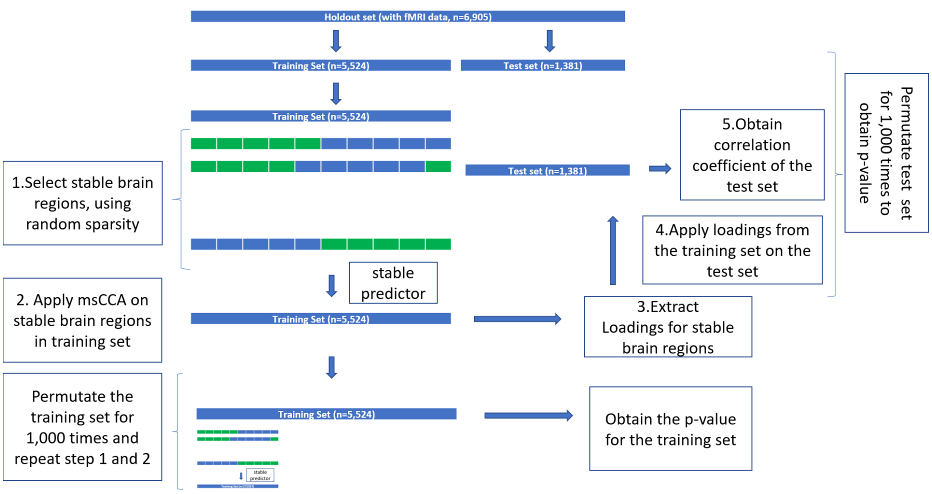
4.3.8.3 Step 3. Identification of the brain signatures correlated to the mental problems and the corresponding satellite-derived physical signatures

Figure 4.5



Note: The identification of brain signatures that correlated to mental problems and satellite-derived physical signatures was conducted within the holdout set. The holdout set was further divided into training and testing sets. The msCCA correlations between brain fMRI data, geographic categories and satellite-derived physical signatures were assessed in the training set and validated in the test set.

Figure 4.6



Note: The analytic pipeline for identifying brain signatures correlated to the mental problems and their physical signatures

Once the correlations between mental problems and satellite-derived physical signatures were established, we sought to identify the brain signatures that correlate the most with mental problems and the identified satellite-derived physical signatures. In order to establish the correlation between three views of data, multiple sparse canonical correlation analysis regression (msCCA) was used (Ing et al., 2019). As an extension of sCCA, msCCA is also vulnerable to overfitting. Therefore, in order to ensure generality, a holdout design was applied in Step 3 as well. Also, in order to prevent double-dipping, Step 3 was only carried out in the holdout set (**Figure 4.5**).

Before data entry, the ROI brain regions were adjusted for sex, age, sites, and total brain volume. The holdout set (n=6,905) was randomly divided into a training set (80%, n=5,524) and a test set (20%, n=1,381).

The msCCA was first applied to the training set. In each msCCA, three views were included in the algorithm: the mental health problems (as behaviour sum scores), identified satellite-derived physical signatures and the 153 ROI brain regions. The msCCA seeks for the brain regions which maximise the cross-correlation coefficient with the mental problem and the identified corresponding physical signature. A sub-sampling procedure was conducted for stability check. In each sub-sampling, 50 % of the training set was drawn and msCCA was applied with random sparsity (0.1-1.0) imposing on the ROI brain regions. The same procedure was repeated 1,000 times, and the non-zero loaded ROI brain regions in each trial were recorded. Only the brain regions appearing above 75 % were considered stable. Then, msCCA was run on the stable ROI brain regions against mental problem and the identified satellite-derived physical signature, to acquire the loadings of stable ROI brain regions and the cross-correlation coefficient. The cross-correlation coefficient is the mean of the correlation coefficients of these three correlations (Ing et al., 2019): correlation (1) between mental health problem and satellite-derived physical signature, (2) between mental health problem and brain signature and (3) between satellite-derived physical signature and brain signature.

The significance level of the cross-correlation coefficient in the training set was ascertained by the permutation test (1,000 times). In the permutation test, two views of the data were randomly ordered, causing a rotation of the relationship among three data views. The same procedure was applied to the rotated data, and the cross-correlation coefficient resulting from each permutation trial was recorded. The p-value was ascertained as the number of permutation trials with a higher cross-correlation coefficient than the original data, divided by the number of permutation trials. The identified brain regions and their loadings were validated in the test set, and the significance level in the test set was ascertained by the permutation test (1,000 times). The analytic pipeline is presented in **Figure 4.6**.

All analyses were conducted using MATLAB (version R2018a; MathWorks)

4.4 Results

4.4.1 Descriptive Statistics

The sample consisted of 279,242 participants (46·87% male). Mean depression score, mean anxiety score, smoking and alcohol intake behaviour are presented in **Table 4.1**.

Table 4.1. Demographics of the whole data set, exploratory set and holdout set.

	Whole Data Set (*SD*)	**Exploratory set (*SD*)**	**Holdout set (*SD*)**
Number	279,242	272,337	6,905
Sex (male)	46.87%	46.83%	48.54%
Age (year)	57 (*7.90*)	57.04 (*7.91*)	55.7 (*7.43*)
Mean Depression (score)	5.47 (*1.99*)	5.47 (*1.99*)	5.31 (*1.84*)
Mean Anxiety (score)	1.64 (*1.48*)	1.64 (*1.48*)	1.57 (*1.46*)
Mean Smoking (score)	0.17 (*0.52*)	0.17 (*0.53*)	0.10 (*0.42*)
Mean Alcohol frequency (score)	3.18 (*1.47*)	3.18 (*1.48*)	3.35 (*1.37*)
Mean Alcohol Intake (unit)	17.28 (*19.93*)	17.27 (*19.96*)	18.05 (*18.92*)
Overdrinking (%)	44.67 %	44.60%	47.44%

The correlations between mental problems are presented in **Table S4.3**.

4.4.2 Step 1 identification of satellite-derived physical signature for each mental problem

The satellite-derived physical signatures of depression (R=0.0551, P<0.001 in the exploratory set, R=0.0395, P=0.003 in holdout set), of smoking behaviour (R=0.0614, P<0.001 in the exploratory set, R=0.05, P<0.001 in holdout set) of alcohol intake amount (R=0.0252 P<0.001 in exploratory set, R=0.0299, P=0.015 in holdout set) and of overdrinking (R= 0.0354, P<0.001 for training set, R=0.0492, P<0.001) were identified via sCCA. Satellite-derived physical signature of anxiety was identified in the exploratory set (R=0.0168, P<0.001), however, it was not validated in the holdout set (R=0.0033, P=0. 77). These physical signatures are tabulated in **Table 4.2**. The correlations among the satellite-derived physical signatures are presented in **Table S4.4**.

Table 4.2. Identified satellite-derived physical signatures of mental health problems.

Band	Type	Wavelength (nm)	Depression	Anxiety	Smoking	Alcohol	Overdrinking
8	UVA	405-420					
9	Blue	438-448					
3	Blue	459-479				-0.2442	-0.4007
10	Blue	483-493					
11	Green	526-536				-0.2367	
12	Green	546-556					
4	Green	545-565				-0.2833	
1	Red	620-670				-0.3950	-0.5109
13	Red	662-672				0.2722	
14	Red	673-683					
15	NIR	743-753					
2	NIR	841-876	-0.7127	-0.7217	-0.5895		
16	NIR	862-877		0.6922			
5	SWIR	1230-1250			-0.5819		
6	SWIR	1628-1652				-0.2933	
7	SWIR	2105-2155	0.7015		0.5602	-0.6985	-0.7606
17	Thermal	10780-11280					
18	Thermal	11770-13480					
	Exploratory		R=0.0551 *P*<0.001	R=0.0168 *P*<0.001	R=0.0614 *P*<0.001	R=0.0252 *P*<0.001	R=0.0354 *P*<0.001
	Holdout		R=0.0395 *P*=0.003	R=0.0033 *P*=0.77	R=0.05 *P*<0.001	R=0.0299 *P*=0.015	R=0.0492 *P*<0.001

4.4.3 Step 2. interpretation of the satellite-derived physical signatures based on the neighbourhood geographic categories

Table 4.3 Interpretation of satellite-derived physical signatures

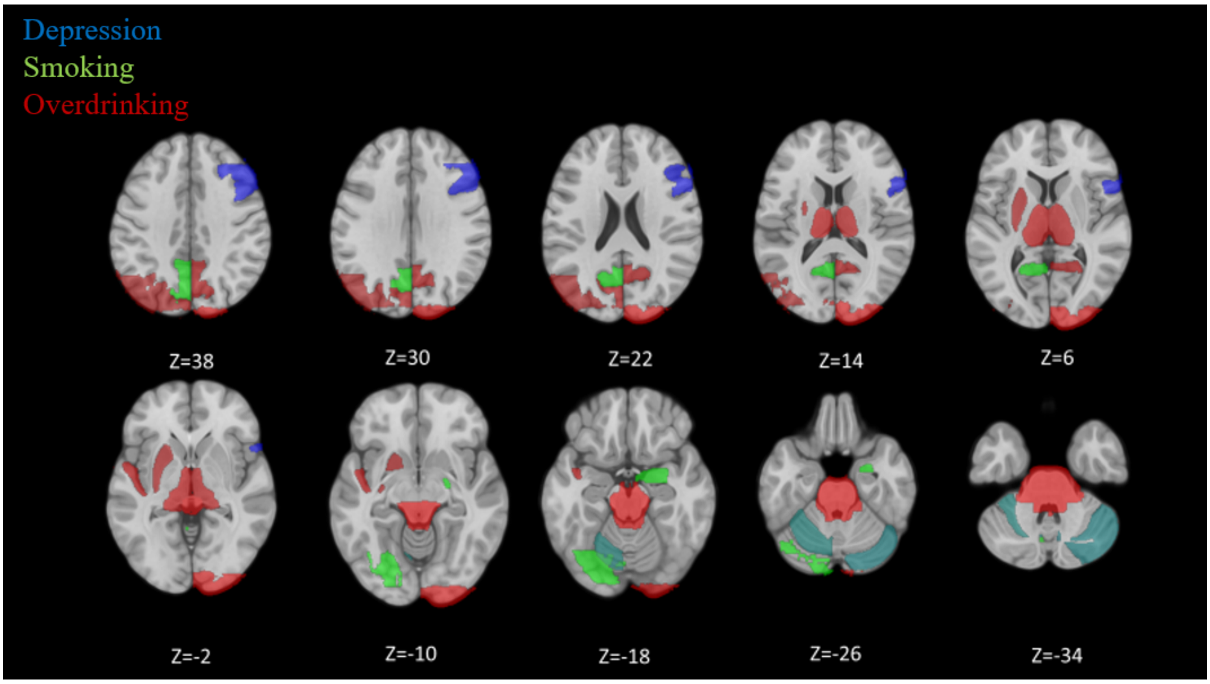
Geographic category	Depression physical signature	Smoking physical signature	Alcohol Intake physical signature	Overdrinking physical signature
Air Pollution	0.4257	0.4145		-0.3463
Greenspace	-0.5377	-0.5385		
Distance to education	-0.3695	-0.381		
Distance to healthcare	-0.3487	-0.3519		
Distance to services	-0.3747	-0.3659	0.2825	
Density of streets	0.3621	0.3678		
Deprivation of income, employment, education			-0.5998	-0.5446
Crime, deprivation of living environment			-0.3211	-0.4170
Density of physical facility (1)			0.4321	
Density of unused land			-0.4221	-0.3125
Density of water			0.3042	0.3083
Distance to factories				0.3423
Density of factories				-0.3157
$R_{training}$	0.6298**	0.6987**	0.3639**	0.3543**
R_{test}	0.6135**	0.6975**	0.3477**	0.3076**

**P<0.001

The interpretation of the satellite-derived physical signatures is illustrated in **Table 4.3**. Within the holdout set, the geographic interpretations were obtained in the training set and were validated in the test set. The satellite-derived depression and smoking physical signatures are positively associated with air pollution and density of streets; and negatively associated with greenspace, distance to education, distance to healthcare and distance to services (depression: $R_{training}$= 0.6298, $P_{training}$<0.001; R_{test}= 0.6135, P_{test}<0.001; smoking : $R_{training}$= 0.6987, $P_{training}$<0.001; R_{test}= 0.6975, P_{test}<0.001). The alcohol intake physical signature is positively associated with density of physical facilities, density of water, distance to services and negatively associated with socioeconomic deprivation, living deprivation, and density of unused lands ($R_{training}$= 0.3639, $P_{training}$<0.001; R_{test}= 0.3477, P_{test}<0.001). The overdrinnking physical signature is positively associated with distance to factories, the density of water, and negatively associated with air pollution, socioeconomic deprivation and living deprivation, the density of factories and density of unused lands ($R_{training}$= 0.3543, $P_{training}$<0.001; R_{test}= 0.3076, P_{test}<0.001).

4.4.4 Step 3. identification of brain signatures correlated to mental problems and satellite-derived physical signatures

Figure 4.7



Note: The brain regions with reduced grey matter volume (GMV) in each mental health problem and its corresponding satellited-derived physical signature were coloured with blue (depression), green (smoking) and red (overdrinking).

In Step 3, the holdout set was divided into a training set (80%, n=5,524) and a test set (20%, n=1,381). msCCA was applied to the training set, and the results were validated in the test set. We identified brain signatures correlated to each mental problem and its corresponding satellite-derived physical signature, shown in **Figure 4.7**.

Reduction of GMV in left inferior frontal gyrus pars opercularis, left juxtapositional lobule cortex, left middle frontal gyrus, and several cerebellar subregions (right crus I, left VI, right VIIb, left and right VIIIa) was associated with the depression physical signature, and the depression score ($R_{training}$=0.0492, $P_{training}$=0.002; R_{test}= 0.0366, P_{test}=0.024, **Table S4.5**). Reduction of GMV in right amygdala, left juxtapositional lobule cortex, right occipital fusiform gyrus, right precuneus cortex and various cerebellar subregions (right crus I, left VI, left and right VIIb, left and right VIIIa, right VIIIb) is associated with the smoking physical signature, and the smoking behaviour ($R_{training}$=0.0598, $P_{training}$<0.001; R_{test}= 0.0597, P_{test}<0.001, **Table S4.6**). Reduced GMV in the brain stem, right cuneal cortex, left frontal operculum cortex, left frontal pole, right insular cortex, right lateral occipital cortex (superior division), left occipital pole, right planum polare, left and right precuneus cortex and left and right thalamus and an overall reduction in the volume of the left and right thalamus is associated with the physical alcohol intake amount signature, and the alcohol intake amount ($R_{training}$= 0.0756, $P_{training}$<0.001; R_{test}= 0.0605, P_{test}=0.001, **Table S4.7**). Reduced GMV in the brain stem, right cuneal cortex, right lateral occipital cortex (superior division), left occipital pole, right planum polare, left precuneus cortex, left putamen, left and right thalamus, and an overall volume reduction in right and left thalamus are associated with the overdrinking physical signature and the overdrinking behaviour. ($R_{training}$= 0.0614, $P_{training}$<0.001; R_{test}= 0.0515, P_{test}<0.001, **Table S4.8**).

4.5 Discussion

In the Neighbourhood Mental Health Map framework, **Chapter 4** focuses on the relationship between Physical Environment and People's Mental Health. There are three novelties in **Chapter 4**. First, we developed a systematic methodological pipeline to identify the physical signatures of mental health problems with satellite raw data. Here, we identified the physical signatures (i.e., geographic patterns) of depression, smoking behaviour and alcohol intake behaviour. Second, we examined the usability of the satellite raw data by interpreting the physical signatures with ground-level geographic information. Third, we predicted the brain structure of specific physical signatures and mental health problems.

4.5.1 Physical signatures of depression are correlated with urban features

The identified depression physical signature was correlated with urban features: less green space, more severe air pollution, high density of roads and proximity to infrastructures ($R_{training}$= 0.6298, $P_{training}$<0.001; R_{test}= 0.6135, P_{test}<0.001). Our results supported other studies reporting a protective association between residential greenness and depression (Sarkar et al., 2018; Song et al., 2019). Instead of using ground-level measurement, most studies employed a satellite-derived, Normalised Difference Vegetation Index (NDVI), to measure green vegetation coverage. NDVI utilises one near infrared (NIR) band and one red band from the MODIS satellite to evaluate the greenness quantitatively and qualitatively. A UKBB study on 122,993 participants with depression has demonstrated a dosage protective effect of green spaces (Sarkar et al., 2018). A Korean study utilised both NDVI and ground-level data and found an inverse association between depression and urban greenness (Song et al., 2019). These studies, however, investigated the association between depression and a specific physical feature (e.g., greenness, NDVI) and may overlook other geographic characteristics. Instead of pinpointing a priori a specific physical measure and focusing only on participants with major depressive disorder, by using the satellite raw data, our approaches aimed at covering the physical environment as comprehensive as possible. The ground-level measurements from UKBB further allowed us to understand the contributing environmental factors in the identified physical signatures. Our results suggested a negative association between depression and green spaces and a positive association between depression and air pollution and the density of streets. Substances causing air pollution mainly include particular matter (PM), carbon oxide (CO), carbon dioxide (CO_2), nitrogen (NOx) and sulfur oxides (SO_2, SO_3). A positive correlation has been shown between air pollution and depression, and a case cross-over study found that air pollution is associated with more depression visits (Lim et al., 2012; Szyszkowicz et al., 2016). Our results also suggested that participants with depressive symptoms reside closer to infrastructural facilities, including education, health care, and other services. Despite being counterintuitive at first glance, the proximity to services can be regarded as a general picture of the urban area, where infrastructural facilities are more densely clustered.

4.5.2 Physical signatures of smoking behaviour are correlated with urban features

The current study demonstrated a high correlation between the smoking physical signature and urban features ($R_{training}$= 0.6987, $P_{training}$<0.001; R_{test}= 0.6975, P_{test}<0.001), which are very similar to the interpretation of the depression physical signature (**Table 4.3**). Despite a minor positive relationship between smoking behaviour and depression (R=0.1053, *P*<0.001, **Table S4.3**), the smoking physical signature and depression physical signature are highly correlated (R=0.9498, *P*<0.001, **Table S4.4**). This indicates that the same physical environment is associated with both depression symptoms and smoking behaviour. In the interpretation step, we found that both depression physical signature and smoking physical signature shared identical geographic characteristics, depicting an urban neighbourhood. Concerning the relationship between the residential environment and the smoking behaviour, previous studies have shown inconsistent results. Some studies showed that residents in rural areas have more frequent usage of cigarettes (Roberts et al., 2017). In contrast, a nationwide German census of 181,324 participants has shown that residents in cities are more likely to be current smokers than in rural areas (Völzke et al., 2006). A Peruvian study investigating smoking behaviour among the urban group, rural group and rural-urban migrant group also reported that inhabitants living in urban areas had a higher lifetime smoking prevalence (Taype-Rondan et al., 2017). However, these studies did not further investigate which urban features are associated with smoking behaviour. Our study demonstrated that less greenness in proximity, higher air pollution, higher density of roads and proximity to infrastructural facilities are positively associated with smoking behaviour.

4.5.3 Reduced grey matter in the posterior cerebellum is correlated with depression and smoking behaviour and their satellite-derived physical signatures

Once we established the relationship between mental problems and the physical environment, we wanted to understand how the brain was correlated to mental health problems and the physical environment. Instead of looking for brain-behaviour and brain-environment association, we applied msCCA to identify the brain regions correlated to both behaviour and environment. Overall, our study showed shared brain signatures between depression-environment and smoking-environment settings, in particular in the cerebellum. We found that the reduction in the volume of posterior regions in the cerebellum (crus I, lobule VI, VIIB and VIIIA) is associated with both the depression physical signature and the smoking physical signature. Apart from coordinating motor functions, the cerebellum is also involved in high-level mental functions. In a fcMRI study recruiting 1,000 healthy participants, it has been shown that around 50% of the cerebellum subregions are associated with cognitive and affective functions (Buckner et al., 2011). The study also showed that the non-motor cerebellar functions are particularly located within the posterior part of the cerebellum

(Buckner et al., 2011). Among the lobules in the posterior cerebellum, it has been reported that subregions VI, VIIB, and VIII are functionally connected to the salience network (Sang et al., 2012). Concerning the role of the cerebellum in mental health, evidence has also shown that reduced GMV in the posterior cerebellum is associated with depression (Grieve et al., 2013). Also, the reduction of GMV in the cerebellum is associated with smoking behaviour (Franklin et al., 2014; Kühn et al., 2012; Wetherill et al., 2015; Yu et al., 2011). Our findings take a step further, proving that the reduction of GMV in these brain regions is correlated to the corresponding satellite-derived physical signatures.

4.5.4 Physical signatures of overdrinking are correlated with suburban features

Regarding the association between residential environment and alcohol intake behaviour, previous studies have conflicting findings. Most of the studies classified the physical environments into urban and rural areas. A study using National Institute on Alcohol Abuse and Alcoholism's National Longitudinal Alcohol Epidemiologic Survey data showed that the prevalence rate of lifetime drinking is higher for the urban adult population than for rural ones (Grant, 1997). Another study has shown that residents living in rural regions have a higher lifetime, twelve-month alcohol intake than those residing in urban areas (Donath et al., 2011). Fone et al. (2013) found that excessive alcohol consumption (3-6 units a day for females; 4-8 units a day for males) appeared more likely in less deprived areas. However, binge drinking behaviour (>6 units/day for females; >8 units/day for males) was more frequent in more deprived areas (Fone et al., 2013). Another study on alcohol intake behaviour in California, USA, reported that the odds of overdrinking (>7 drinks/week for females and >14 drinks/week for males) were higher for inhabitants residing in the least deprived regions (Pollack et al., 2005). Our findings suggested that in less economically and less socially deprived areas, residents tend to have more alcohol intake, and overdrinking is also more frequent. The alcohol intake geographic features (higher density of physical facility, higher density of services, water-rich and used-land-rich) are hard to classify into urban/rural dichotomy. However, the overdrinking physical signature depicts a factory-scarce, water-rich, less air-polluted area, representing an affluent, suburban residential environment. Of note, the associations between the alcohol intake/overdrinking physical signatures and their geographic features were much lower than the correlation between depression/smoking physical signatures and their corresponding geographic features. The relatively low correlation between satellite-derived physical signatures and interpretation implied that other unmeasured environmental characteristics also contribute to the physical signatures of alcohol intake behaviour and overdrinking.

4.5.5 Reduced grey matter in multiple brain regions is correlated with excessive alcohol intake and its physical signature

In the present study, we also investigated the brain signatures of alcohol intake amount and overdrinking and their corresponding physical signatures. In both settings, the reduction of GMV in the brain stem, right cuneal cortex, left occipital pole, right planum polare, left precuneus cortex and thalamus was found. Neuroimaging studies have shown that alcohol intake is associated with global brain volume reduction (Harper & Kril, 1985; Jernigan et al., 1991). Evidence has shown that volume reduction in the grey matter of the cuneal cortex, precuneus cortex, thalamus and putamen is associated with excessive alcohol consumption (Grodin et al., 2013; Mechtcheriakov et al., 2007; Rando et al., 2011; van Holst et al., 2012). A previous study has reported that GMV reduction around the parietal-occipital region, including the cuneal cortex and the precuneus cortex, can predict early relapse of alcohol usage (Rando et al., 2011). Some specific regions have been reported to be negatively correlated with heavy drinking: insular cortex, putamen, thalamus, hippocampus, nucleus acumbens (Durazzo et al., 2011; Shim et al., 2019).

In the present study, reduction of GMV and decreased volume of the thalamus were found in both settings. Thalamus is the key node of the two most affected brain networks in alcoholism: the Pepez circuit and the frontocerebellar brain network. Shrinkage of the thalamus is frequent in alcohol abusers and is one of the key findings in Korsakoff syndrome, a complication of chronic excessive alcohol intake. It was also shown that the effect of alcohol on the thalamus is graded from uncomplicated alcoholics to patients with Korsakoff syndrome (Sullivan & Pfefferbaum, 2009). Apart from being aligned with previous findings in the literature, our results indicate further that the reduction of GVM in certain areas and volume shrinkage of the thalamus are additionally associated with the physical environment.

4.5.6 Limitations

The findings presented in **Chapter 4** should be interpreted in light of several limitations. First, although we interpreted the satellite-derived physical signatures with ground-level geographic data, it should be noted that there might be other geographic features that were not included in the UKBUMP dataset. In other words, the interpretation can be incomplete. Studies in earth science can further clarify what these linear combinations of light bands in satellite-derived physical signatures connotate. Second, the statistical tool we used to detect satellite-derived physical signatures could only detect linear relationships. Future studies should also adopt non-linear methods and compare the findings.

4.5.7 Conclusion:

There are several strengths in the study presented in **Chapter 4**. The novel application of the satellite raw data provides a simple tool for identifying the physical signatures of mental problems. Using the UKBUMP data, we linked the satellite-derived physical signatures to ground-level data, gaining more insight into the interpretation. This novel approach allows us to monitor mental health issues globally in real-time and overcome administrative boundaries. Moreover, this study further identified brain volume changes in different environment-symptom conditions, providing evidence of the association between behaviour, physical environment, and brain structure.

Our findings suggested that depression and smoking satellite-derived physical signatures shared urban neighbourhood features, while the overdrinking physical signature showed a neighbourhood with suburban features. Moreover, the brain features correlated to the mental problems and their satellite-derived physical signatures were identified.

CHAPTER 5: Social structure, social mechanism and development of conduct disorder

5.1 Abstract

5.1.1 Background

Detrimental social structure in the neighbourhood (e.g., socioeconomic deprivation) and low levels of social mechanism (e.g., low social cohesion and informal social control) are believed to synergically contribute to the development of conduct disorder (CD) behaviours (e.g., stealing). Nevertheless, the social structure has rarely been modelled in a longitudinal manner. Also, social structure is often solely based on socioeconomic deprivation and does not include other indicators (e.g., education, crime, environment). In addition, previous research often used summed scores of behaviours to describe CD behaviours. These studies did not assess the interaction between particular CD behaviours and low levels of neighbourhood social cohesion, informal social control and other social risks (e.g., affiliating with deviant peers) under different levels of longitudinal exposure to detrimental social structure. The aims of the study in **Chapter 5** are twofold. First, we aimed to identify latent transitions of longitudinal deprivation patterns based on census-level data. Second, we sought to examine, in network models, interactions between CD behaviours and social cohesion, informal social control and deviant peer affiliation.

5.1.2 Materials and methods

Latent transitions of neighbourhood-level deprivation patterns (e.g., high vs low), based on census-level information, were estimated between age 12.5 and 15.5. In network models, we used multi-informant variables and estimated interactions between caregiver-reported CD

behaviours and child-reported social cohesion, informal social control and affiliation with deviant peers within the different patterns of the latent neighbourhood-level deprivation transitions. Then, using a permutation-based network comparison test, we tested whether the strength of the interactions in the whole network (i.e. global strength) was greater in a particular latent neighbourhood-level deprivation transition than others.

5.1.3 Results

Three constant deprivation patterns: deprived (n=485), intermediate (n=1,467) and low (n=2,085) patterns were identified. In the deprived pattern, “bullying” was the most influential CD behaviour; it had the highest interaction with lack of social cohesions, social control, and deviant peer affiliation. In contrast, non-violent CD behaviours were important in the intermediate (i.e. “lying") and low (i.e. “staying after dark“) patterns. Social cohesion had a protective role in CD behaviours development in all deprivation patterns. Affiliation with deviant peers involved in property delinquency was the greatest risk factor in CD behaviours development in all deprivation patterns. Of interest, the global strength indicated that the strongest interactions (statistically) were located in the intermediate pattern, suggesting greater variability in the deprived and low patterns.

5.1.4 Conclusion:

Our model revealed three longitudinal neighbourhood-level deprivation patterns in which the most influential CD behaviour varied in seriousness in a step-like manner. Regardless of neighbourhood-level deprivation patterns, affiliation with peers involved in the burglary was the most important risk factor for CD behaviours. In contrast, social cohesion played a protective role against CD development.

5.2 Introduction

In the study presented in **Chapter 5**, we will go a layer beneath the physical environment to the social environment (i.e., social structure and social mechanism in the Neighbourhood Mental Health Map), and investigate how social environment interacts with people's mental health (**Figure 1.5**). More precisely, **Chapter 5** focuses on how social mechanisms interact with adolescents' mental health, particularly the conduct disorder behaviours (CD: lying, fighting, stealing), in the context of social structure.

CD behaviours are a costly mental health disturbance that burdens the welfare system. Adults with a history of persistent CD behaviours in childhood account for 25% of monthly welfare expenses (Rivenbark et al., 2018). Also, CD can negatively impact the victims' lives and disrupt an individual's life course and future opportunities (Fergusson & Horwood, 1998; Mordre et al., 2011). For instance, CD behaviours in adolescence can predict criminal behaviours, violence and substance use in adulthood (Odgers et al., 2008). According to the Global Burden of Disease Study 2010, CD is one of the primary causes of disability, especially among children (Erskine et al., 2014). In order to prevent CD and reduce potential ensuing welfare costs, it is warranted to understand how it develops (Fairchild et al., 2019).

Like many other mental problems, CD also has a complex aetiology. One of the potential risk factors for CD is the environment where children grow (Fairchild et al., 2019). Previous findings have found a positive correlation between familial environment (e.g., parenting style), schools, peer affiliation and CD development (Fairchild et al., 2019; Lacourse et al., 2006; Rinaldi & Howe, 2012). However, it should be noted that familial environment, schools and peer affiliation are all embedded in a broader environment: *neighbourhood*. For decades, scholars have been investigating the role of the neighbourhood in CD development. The neighbourhood is important for two reasons. First, the neighbourhood plays a contextual role for other environments (e.g., familial environment, school). Second, children and adolescents often spend much time socializing with peers in neighbourhoods without adults' supervision (Matthews & Limb, 1999; Tompsett et al., 2016). Hence, it is considered that both the neighbourhood quality (i.e., social structure) and the types of interactions taking place within the neighbourhood (i.e., social mechanism) are crucial for CD developments (Elliott et al., 2015). One of the indicators for social structure in a given neighbourhood is the neighbourhood deprivation level. Although *deprivation* is often described as an economic characteristic, it should be noted that the term bears a broader connotation, including unemployment, education, social disorder (e.g., neighbourhood crime activities) and living environment (Visser et al., 2021). Previous studies have demonstrated associations between low neighbourhood-level socioeconomic status and CD behaviours (Beyers et al., 2001; Martinez & Polo, 2018). Also, a growing body of evidence shows a positive association between the high perceived social disorder and CD behaviours (Li et al., 2017; Singh & Ghandour, 2012). It is suggested that children and adolescents modify their behaviours to meet the "street code" and demonstrate invulnerability (Anderson, 1997; McNeeley & Wilcox, 2015). This is supported by the empirical studies, demonstrating that deviant peer affiliation is one of the most robust predictors for CD behaviours (Chen et al., 2015; Roosa et al., 2005).

Nevertheless, previous evidence showed that neighbourhood deprivation is not directly associated with delinquency (Sampson et al., 1997). This observation raised the concern of how neighbourhood deprivation relates to CD behaviours, which also include delinquent behaviours. Sampson et al. (1997) argued that social cohesion and informal social control link structural deprivation and high crime rates. Social cohesion is the bonds of trust between inhabitants in the neighbourhood, including a friendly atmosphere and readiness to help other residents. Informal social control is the ability to mobilize in a given neighbourhood and willingness to intervene in misconduct on behalf of others (Sampson et al., 1997). Sampson et al. (1997) combined social cohesion and informal social control into the concept of *collective efficacy*.

Previous evidence has shown that high social cohesion and informal social control can protect children residing in deprivation from CD behaviours development (Odgers et al., 2009; Sharma et al., 2019). In the Neighbourhood Mental Health Map, instead of collective efficacy, we use the term *social mechanism* to embody social cohesion, informal social control, and deviant peer affiliation. The term social mechanism emphasizes that this interpersonal mechanism is embedded in a broader social structure layer (**Figure 1.5**).

Although these studies haved advanced our knolwedge of neighbourhood-level risks and the CD development, there are still gaps in our understanding of CD behaviours development, in particular the interaction with the social mechanism in the context of social structure (i.e., neighbourhood deprivation). First, only limited studies have employed repeated measures of neighbourhood deprivation (Kleinepier & van Ham, 2018; Kleinepier et al., 2018; Wheaton & Clarke, 2003). Most studies used a cross-sectional design, therefore, were unable to evaluate the deprivation exposure longitudinally (Bush et al., 2010; Lawler et al., 2017; Oberle et al., 2011; Patalay & Fitzsimons, 2016; Singh & Ghandour, 2012). Sharkey & Faber (2014) and Lund (2020) pointed out that prolonged deprivation exposure in childhood greatly impacts the later life course. This includes low educational attainment in adulthood, a decisive factor for future qualifications and employment (Bardone et al., 1996; Fairchild et al., 2019; Lund, 2020; Vergunst et al., 2019). Also, the usage of objective longitudinal data of neighbourhood deprivation is essential since participants could move from one place, experiencing different levels of deprivation (Flouri et al., 2013). Moreover, even if participants stay within the same neighbourhood; the deprivation level might change over time due to changes in demographic structure, economic growth, recession or new policy

(Atkinson, 2000; Costello et al., 2003; Gennetian & Miller, 2002). Hence, it is paramount to use repeated census-level deprivation indicators to account for the longitudinal deprivation exposure and model the social structure longitudinally.

Second, most studies treated neighbourhood deprivation as a synonym for neighbourhood-level socioeconomic status or crime (Damm & Dustmann, 2014; Kleinepier & van Ham, 2018; Kleinepier et al., 2018; Wheaton & Clarke, 2003). Such studies often overlooked other deprivation indicators, e.g., education, health, and the quality of the living environment (e.g., indoor heating and outdoor air quality), which can be contributing factors to CD development. For instance, it has been found that children exposed to higher air pollution have elevated CD behaviours (Roberts et al., 2019). Also, neighbourhood-level education attainment is a vital neighbourhood feature because it often indicates the social class in a given neighbourhood. Evidence showed that living in neighbourhoods with a higher proportion of inhabitants with higher education attainment is associated with fewer CD behaviours (Sampson et al., 2019). Given that many types of deprivation can contribute to CD behaviours development, it is paramount to include an extensive range of repeated census-level deprivation indicators to reflect the multifacetedness of social structure.

Third, previous research has primarily relied on sum scores of CD behaviours (e.g., delinquent behaviours). This approach, however, ignores the heterogeneous nature of different kinds of CD behaviours. For example, aggressive behaviours (e.g., physical abuse) differ in severity from other non-violent behaviours (e.g., lying). It is plausible that different CD behaviours can interact with social structure and social mechanisms differently. To date, little is known about how each CD behaviour interacts with different social mechanisms within varying longitudinal social structures (i.e., deprivation patterns).

5.2.1 Purpose of this chapter

The purposes of **Chapter 5** are twofold. First, using the Avon Longitudinal Study of Parents and Children (ALSPAC) cohort, we aimed to examine the longitudinal exposure to detrimental social structure (i.e., a range of aspects of neighbourhood deprivation) in adolescence. To achieve this, we employed the latent transition analysis (LTA) on census-level neighbourhood data, seeking to model longitudinal neighbourhood-level deprivation patterns, which can be consistent, increasing, decreasing and low. Second, by using network analysis, we sought to investigate the interactions between CD behaviours and social mechanisms in the context of social structure (i.e., model longitudinal neighbourhood-level deprivation patterns). Here, the social mechanisms include social cohesion, informal social control, and deviant peer affiliation. Hence, in the Neighbourhood Mental Health Map framework, **Chapter 5** contributes to understanding the interactions between social environment and mental health, particularly in adolescents.

5.3 Materials and Methods

5.3.1 Participants

Avon Longitudinal Study of Parents and Children (ALSPAC) is a multigenerational cohort of 14,541 pregnancies between April 1991 and December 1992 in the greater Bristol area, United Kingdom. When the oldest children were seven-year-old, ALSPAC bolstered the sample size and included more cases who had not participated in the cohort. Therefore, 15,454 pregnancies were included, and 14,901 of the child reached the first year of life. The ethical approval was granted by the ALSPAC Ethics and Law Committee and the Local Research Ethics Committees (Boyd et al., 2013; Fraser et al., 2013). Participants' informed consent was obtained for the use of data collected via the questionnaires and clinics. Details and data of this cohort are available on the ALSPAC website: http://www.bristol.ac.uk/alspac/

In the present study, 14,129 children with complete Index of Multiple Deprivation data (IMD) were selected for the LTA classification of deprivation patterns. 4,037 children with complete IMD data, outcome measures (CD behaviours, social cohesion, informal social control, and deviant peer affiliation), information on family adversity, and consistent LTA deprivation pattern were selected for the network analysis. The study website contains details of all the data that is available through a fully searchable data dictionary and variable search tool (webpage: http://www.bristol.ac.uk/alspac/researchers/our-data/).

5.3.2 Measures

*Neighbourhood deprivation***.** The measures of neighbourhood deprivation for age 12.5 and 15.5 were extracted from the census-level UK Index of Multiple Deprivation (IMD) data collected in 2004 and 2007, respectively. IMD 2004 and IMD 2007 were scores based on 32,482 Lower Super Output Areas (LSOA) in England and cover seven domains: (1) income, (2) employment, (3) health deprivation & disability, (4) education, skills & training, (5) barriers to housing & services, (6) crime and (7) living environment (quality of housing and outdoors environment). To assess deprivation patterns across time, we employed these seven domains and examined their changes over time. In ALSPAC, for data protection reasons, the original scores of ALSPAC domains were transformed to quantile ranging from 1 (the least deprived) to 5 (the most deprived).

Conduct disorder behaviours. Seven CD behaviours from adult-based Development and Well-Being Assessment (DAWBA) at age 15.5 were included in this study (Goodman et al., 2000). These were knowledge from the caregivers, whether the participant, in the past 12 months, had frequently “told lies”, “started fights other than with siblings”, “bullied/threatened people”, “stayed out after dark much later than supposed to”, “stolen from house/others/shops", "run away from home more than once or stayed away all night without permission" and "played truant". The response categories for each item were 1: No, 2: perhaps, 3: definitely. In order to examine the general level of CD behaviours at different deprivation patterns and validate previous findings, a sum score of CD behaviours for each participant was also calculated to reflect the severity of CD behaviours.

Social mechanism factors included in this study emcompassed three domains: social cohesion, informal social control and deviant peer affiliation.

Social cohesion. Four items rated by adolescents with the Edinburgh Study of Youth Transitions and Crime (ESYTC, Smith & McVie, 2003) at age 15.5 were included. These were: the number of adult neighbours "that are friendly", the participant "talks to, at least once a month", "feels they could ask for help" and the number of "young people that are friendly". The response categories for each item were 1: None, 2: One or some, 3: Most or all. In order to examine the general level of social cohesion in different deprivation patterns, a sum score of social cohesion for each participant was also computed to reflect the general level of social cohesion perceived by the participants.

Direct and indirect informal social control. Eight items from the ESYTC Computer Task at age 15.5 (Smith & McVie, 2003) were included for assessing the level of direct and indirect informal social control (Gau, 2014; Warner, 2007): the likelihood that an adult would directly "try to move on young people" or indirectly intervene by trying to "call the police" if the young people were "hanging around the streets", "writing/spraying paint", "shouting/swearing at adults", "fighting in the street". The response categories for each item were recoded as 0: "Not at all likely", 1: "Not very likely", 2: "Fairly likely", 3: "Very likely". "Not sure" was coded 1.5 as it was the mean of the response categories. Sum scores of two types of informal social control were calculated to represent the perception of the direct and indirect informal social control of each participant.

*Affiliation with deviant peers***.** Nine types of peer's delinquency were self-reported by the youth at age 15.5 in ESYTC Computer Task (Smith & McVie, 2003). These items were: whether some of the participant's friends "broke into the house", "broke into the car", "rode a stolen car", "sold an illegal drug", "hit or picked on others", "kicked/punched/attacked others", "carried a knife or other weapons", "hurt and injured animal or bird on purpose", and "the number of friends that took drugs". The response categories for "the number of friends that took drugs" were coded as 0: "None", 1: "One or some", 2: "Most or all". The response categories for the rest of the items in affiliation with deviant peers were coded as 0: "No", 1:"Yes". Exploratory factor analysis was employed to regroup these items into three factors: "friends involved in burglary", "friends involved in drug offence", and "friends involved in the perpetration of physical abuse" (**Figure S5.1**).

5.3.3 Covariates

CD behaviours, measures for social cohesion, direct and indirect informal social control, and affiliation with deviant peers were controlled for sex and early exposure to family adversity based on the Family Adversity Index questionnaire (Bowen et al., 2005). In ALSPAC, family adversity was evaluated at three time points. These time points were: (1) the second trimester of pregnancy, (2) between birth and age two, and (3) between age two and age four. Eighteen contextual adversity factors were evaluated, including financial difficulties, housing, substance abuse, and criminal involvement, whether the mother and the child were exposed (recorded as 1) or not (recorded as 0). A cumulative score was created to reflect the overall adversity at each time. In this study, family adversity at each time was rescaled (from -1 to 1) and summed up to compute a cumulative family adversity score.

5.3.4 Statistical analysis

5.3.4.1 Step 1 Latent transition and validation

The study was conducted with two main steps. Step 1 was the validation step. More specifically, latent transition analysis (LTA) was estimated to identify different deprivation patterns. The aim was to use the whole range of deprivation domains across two time points to identify different deprivation patterns. LTA was applied to the participants with complete IMD data (n=14,129). LTA is an extension method of latent class analysis and can identify whether the participants kept or changed latent class across time. AIC, BIC and SABIC are often used to ascertain the optimal model. However, scientific relevance and parsimony should also be considered (Collins & Lanza, 2009, p.190; Ruppert et al., 2003, p.221). Hence, to ensure the ability to validate the LTAs, our decision was also guided by a sufficient sample (> 0.5%) for each "stayers" or "movers" pattern. The quality of separation was assessed with entropy. Conventionally, entropy greater than 0.8 is considered a clear separation between latent classes. The LTA was performed in Mplus (Version 8; Muthén & Muthén, 2010). With regard to validation, we employed a non-parametric permutational analysis of covariance (ANCOVA) to examine the differences between the LTA patterns.

Here, we tested whether summed scores for conduct disorder, social cohesion, indirect and direct types of informal social control, and factor scores of deviant peer affiliation were different between LTA patterns (Gau, 2014; Warner, 2007). Sex and early adversity were included as covariates. We used a non-parametric permutation test (iteration = 10,000) to determine the significance level. In order to identify in which deprivation patterns occurred the difference, a post hoc permutation test with Bonferroni correction (iteration = 10,000) was used. The ANCOVA described in this section was performed in RStudio (R_Core_Team, 2013).

5.3.4.2 Step 2 Network analysis

In order to assess the interactions between CD behaviours and social mechanism factors (i.e., social cohesion, informal social control and deviant peer affiliation) in the context of different LTA patterns, network analyses were conducted. The social mechanism factors that significantly differed between deprivation patterns in Step2 were selected for the network analysis. For each deprivation pattern, Gaussian Graphical Model (GGM) was estimated by employing the R package, *qgraph* (Epskamp et al., 2012). In a GGM network, every edge between two nodes is a conditional independence relationship (i.e., partial correlation) (Schellekens et al., 2020). In order to ascertain the influence of each node on the whole network (i.e., centrality), the R package *networktools* was employed to assess the 1-step bridge expected influence. The 1-step bridge expected influence is the sum of all loadings on the edges that link the specific node in a predefined community to other nodes located in other communities (Jones et al., 2021; Opsahl et al., 2010). In other words, the 1-step bridge expected influence does not take the interconnections within the same predefined community into account. Since the original signs of the edge loadings stayed the same when computing the 1-step bridge expected influence, it can be viewed as a cumulative impact on the activation of the network (Robinaugh et al., 2016). In the network analysis, the items were regrouped as nodes into two communities: “CD community” and “social mechanism community”. Seven CD items (nodes) contributed to the “CD community”. Four social cohesion items (nodes), eight informal social control items (nodes) and two summarized deviant peer affiliation factors (peers involved in burglary and physical abuse) formed the “social mechanism community”, ending up with 14 nodes. It should be noted that “social mechanism community” did not include factors summarizing deviant peer affiliation with drug offenders since no significant difference was found between deprivation patterns. Nodes having the top 15% 1-step bridge expected influence in the whole network were regarded as bridge nodes that play an important role in the network's activation. The network stability was dertermined by a case-dropping bootstrapping (n boots = 1,000) via the R package *bootnet* (Epskamp et al., 2018, **Figure S5.2**). The statistical assessment of the difference between deprived, intermediate and low networks was based on the permutation-based Network Comparison Test (NCT, van Borkulo et al., 2016). NCT assesses the difference in interconnectivity between nodes (i.e., global strength) between two networks. Global strength is the sum of absolute weights of all edges in a network, representing the overall network connectivity. Hence, the difference in global strength between two networks demonstrates the difference in overall connectivity between two networks. All network analyses described in this section were performed in RStudio (R_Core_Team, 2013).

5.4 Results

5.4.1 Step 1: Latent transition analysis uncovered constant deprived, intermediate and low patterns.

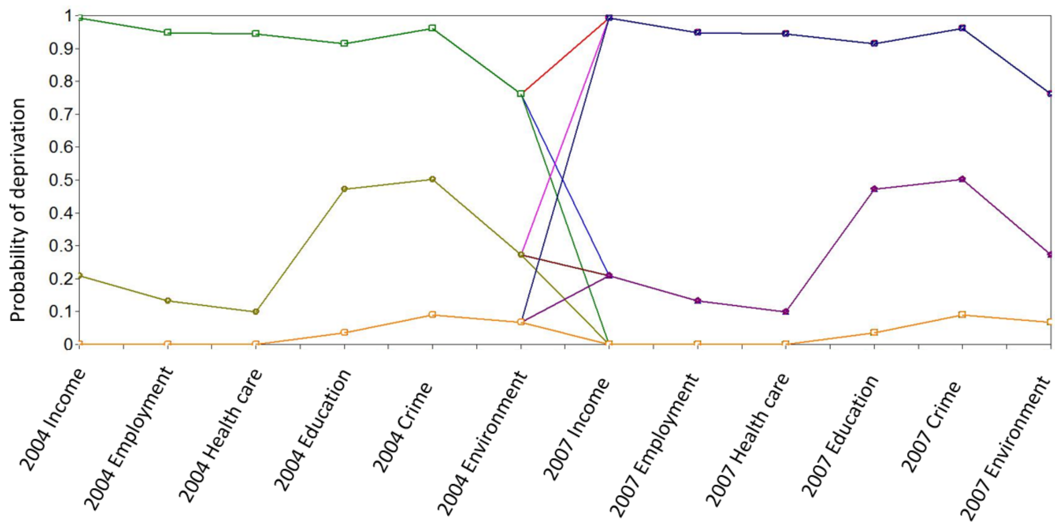
In Step 1, three-class and four-class LTAs were modelled on the participants with complete IMD data (n=14,129). The initial models found little differentiation in the domain "barriers to housing & services" between different latent class patterns. Hence, we removed this domain and only modelled the longitudinal patterns of the remaining six domains (i.e., income, employment, health deprivation & disability, education, skills & training, crime and living environment). Also, it was revealed that the latent class patterns were very similar between the three-class model and the four-class model. In both models, participants have classified into a constant deprived pattern (constantly deprived in all IMD domains over time), a low pattern (constantly not deprived in all IMD domains over time), intermediate patterns which were constantly intermediately deprived in IMD education and crime domains over time and the cross-over patterns between these three levels of deprivation.

The AIC, BIC and SABIC (**Table S5.1**) showed that the four-class model had a better fit. Nevertheless, both three-class and four-class models comprised continuous exposure to deprived, intermediate and low patterns. The only difference was the number of intermediate patterns. The four-class model was composed of two similar intermediate patterns, whereas the three-class model is composed of one. Therefore, we adopted the parsimonious model (three-class LTA model, **Figure 5.1**) in the present study. The three-class model had an entropy of 0.963, meaning that there was a good differentiation between patterns (>0.8). The latent transition probabilities in the three-class model are presented in **Table S5.2**.

The constant patterns are so-called “stayer” patterns, meaning that the participants had experienced a constant deprivation level (or lack of deprivation) over time. Of note, the intermediate deprivation pattern showed a deprivation only in the domains “education” and “crime”.

The cross-over patterns between the three deprivation levels were the six “mover” patterns. These “movers” had experienced a change in deprivation over time. Yet, non of the “movers” patterns had a proportion greater than 5% in the ALSPAC sample (**Table S5.3**). Therefore, only the participants from the “stayer” patterns were analyzed in this study (i.e., constant deprived, intermediate and low pattern).

Figure 5.1



Note: Latent transition analysis on deprivation domains in the year 2004 and 2007.

Participants from “stayer” patterns and having complete measures were selected for validation analysis and network analysis. The demographic of the data included in this study is presented in **Table 5.1**.

Table 5.1

		Complete (n=4,037)	Deprived (n=485)	Intermediate (n=1,467)	Low (n=2,085)	Comparison†
Covariates						
Sex, male (%)		1,930 (47.81%)	206 (42.47%)	704(47.99%)	1,020(48.92%)	
Early adversity sum score (mean, *SD*)		-0.2096(*2.32*)	1.15(*2.84*)	-0.21 (*2.29*)	-0.52(*2.09*)	
CD and Social mechanism (mean, *SD*)						
Conduct disorder		7.66(*1.43*)	7.95(*1.83*)	7.71(*1.46*)	7.55 (*1.29*)	Dep>Int>Low
Social cohesion		9.23(*1.63*)	8.96(*1.67*)	9.19(*1.66*)	9.33(*1.59*)	Low>Int>Dep
Direct informal social control (move on)		7.15(*2.16*)	6.28(*2.22*)	7.10(*2.06*)	7.40(*2.16*)	Low>Int>Dep
Indirect informal social control (call police)		6.89(*2.06*)	6.50(*2.09*)	6.88(*1.98*)	6.99(*2.10*)	Low≥Int>Dep††
Deviant peer (factor score mean, *SD*)						
Friends involved in	Burglary	0(*0.94*)	0.2(*1.34*)	-0.011(*0.91*)	-0.04(*0.83*)	Dep>Int≥Low††
	Drug offence	0(*0.86*)	0.12(*0.92*)	0.004(*0.86*)	-0.03 (*0.84*)	No difference†††
	Perpetration of physical abuse	0(*0.84*)	0.15(*0.97*)	-0.001(*0.83*)	-0.03 (*0.81*)	Dep>Int≥Low††

Note: Demographic of the complete, deprived, intermediate and low datasets

† Comparison is based on ANCOVA, controlled for sex and early adversity sum score.

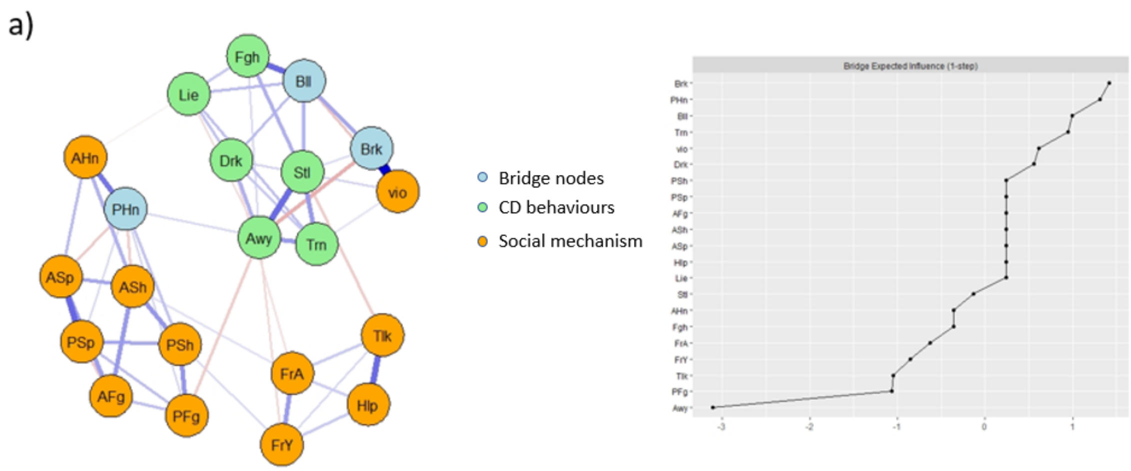
†† No significant difference was revealed between Int and Low.

††† ANCOVA did not reveal a significant difference between Dep, Int and Low in deviant peers involved in drug offences ($F = 2.521$, $P = 0.0772$)

In the validation step, ANCOVA was employed for assessing whether the conduct disorder and environmental risk factors varied at different deprivation levels. Our results revealed that conduct disorder increased as the deprivation rose. Social cohesion and informal social control diminished as deprivation increased. As for the deviant peer affiliation, we identified two peer types (burglars and physical abuse perpetrators) that were more prevalent in higher deprivation patterns. Of note, ANCOVA did not show a significant overall difference in peers involved in drug offences across different deprivation patterns ($F = 2.521$, $P = 0.0772$, **Table S5.4**).

5.4.2 Step 2: Network analysis revealed bridge nodes in deprived, intermediate and low networks.

Figure 5.2



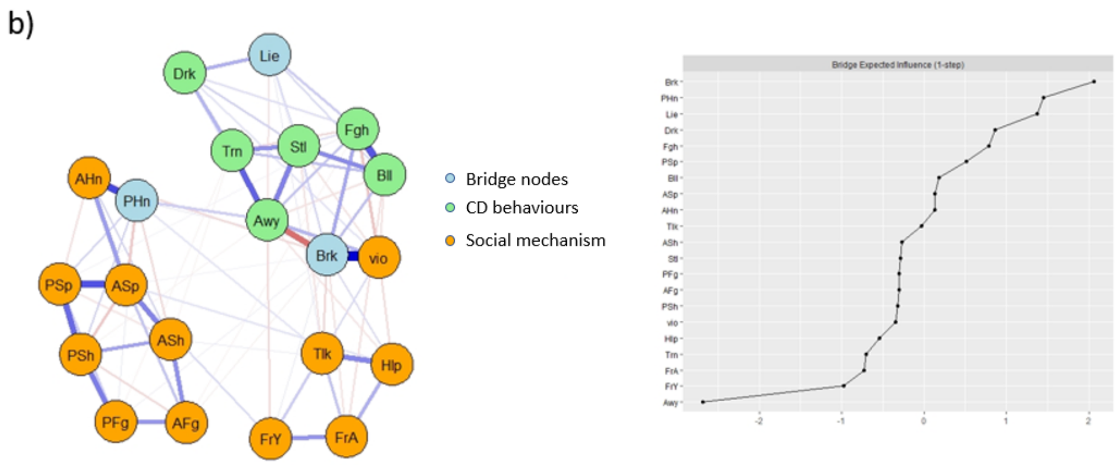
Note: The most influential factors (bridge nodes) in areas with deprived pattern were: "friends involved in burglary" (Brk), adults call the police if young people were hanging around the streets (PHn), and adolescents "bullied/threatened people" (Bll).

Network analysis identified three nodes (blue) bridging conduct disorder behaviours (CD community, green) and social mechanism factors (social mechanism community, orange) in each deprivation pattern (**Figure 5.2, 5.3, and 5.4**).

Across all deprivation patterns, affiliation with burglar peers ("friends involved in burglary", Brk) had the greatest bridge expected influence. Also, across all deprivation patterns, one type of indirect informal social control was the second most influential bridge node ("adults call the police if young people were hanging around the streets, PHn).

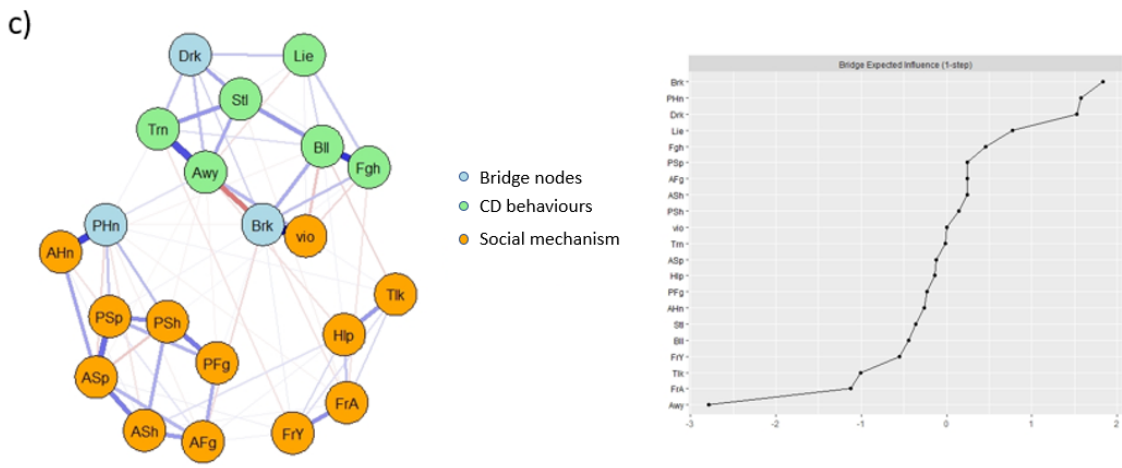
Yet, the CD behaviour bridging social mechanism and other CD behaviours differed across LTA deprivation patterns. On the one hand, in the deprived pattern, the bridging CD behaviour was bullying ("bullied/threatened people", Bll). On the other hand, non-violent CD behaviours were bridge CD behaviours in the intermediate (i.e. “told likes”, Lie) and low (i.e. “stayed out after dark much later than supposed to”, Drk) patterns, respectively.

Figure 5.3



Note: The most influential factors (bridge nodes) in areas with intermediate pattern were: “friends involved in burglary” (Brk), adults call the police if young people were hanging around the streets (PHn), and adolescents “told likes” (Lie).

Figure 5.4.



Note: The most influential factors (bridge nodes) in areas with low pattern were:

“friends involved in burglary” (Brk), adults call the police if young people were hanging around the streets (PHn), and adolescents “stayed out after dark much later than supposed to” (Drk).

Of interest, social cohesion, particularly the attitude of neighbours (i.e., “adults who are friendly” and “young people who are friendly”), had a negative-weighted bridge expected influence in all deprivation patterns. Also, they ranked at the bottom in the bridge expected influence, implying their mitigating role in the networks, hence a protective role counteracting the CD behaviour development. In contrast, factors belonging to informal social factors could be positive (e.g., PHn) or negative (e.g., PFg) in bridge expected influence, implying that they could serve as risk factors (when positive) or protective factors (when negative).

As for the interconnectivity, our findings showed that the global strength (GS=13.45) of the intermediate network was significantly greater than that of the deprived network (GS= 11.10, Difference = 2.35, P=0.012). Yet, we did not find a significant difference in GS between the low and the deprived networks (Difference = 1.38, P=0.122) or between the low (GS= 12.48) and the intermediate network (Difference = 0.97, P=0.08).

5.5 Discussion

The present study explored the links between CD behaviours and social mechanisms (i.e., social cohesion, informal social control and deviant peer affiliation) within different social structures (i.e., neighbourhood deprivation pattern). To our knowledge, the present study is one of the first studies investigating the longitudinal latent deprivation patterns employing a range of deprivation domains (i.e., income, employment, health deprivation & disability, education, skills & training, crime and living environment). This study added to the current knowledge of the relationship between CD behaviours, social mechanisms and social structure in three ways.

5.5.1 First finding: social mechanism is better in less deprived social structure

Our first finding is related to the validation of previous studies. The association between the consistent deprivation patterns and social mechanisms (i.e., social cohesion, informal social control and deviant peer affiliation) generally follows a step-like manner. That is, the higher the deprivation level, the worse the social mechanisms (i.e., lower social cohesion, lower informal social control and higher deviant peer affiliation). Also, the present findings did not show many participants having moved across different neighbourhood deprivation patterns. In other words, the vast majority of families remained at the same level of deprivation between ages 12.5 and 15.5. Admittedly, one of the initial attempts was to identify the participants who have changed deprivation exposure levels across time. However, this finding is in line with the UK's Millennium Cohort Study (MCS) results. MCS sought to explore the roles of neighbourhood deprivation and mobility in children’s behaviour problems. Although one-third of the families did report moving from one place to another, the findings showed that they often moved into a neighbourhood with similar characteristics, including deprivation levels (Flouri et al., 2013). Mobility between deprived and non-deprived areas was rare (Flouri et al., 2013). Similar findings were also shown in the Project on Human Development in Chicago Neighborhoods (Sharkey, 2012). Sharkey (2012) revealed that if the participants moved, they often moved to the neighbourhoods with similar ethnic and socioeconomic features as their former environment. This preference can account for our findings, showing that very few participants had experienced a change in exposure to deprivation.

5.5.2 Second finding: protective and risk social mechanism factors for CD development were identified

Second, deprivation networks were modelled for the identification of the most crucial social mechanism factors contributing to CD behaviours development. Also, by using network analysis, we demonstrated putative protective factors that can mitigate CD behaviours development. For validation, we further examined whether the level of social mechanism (i.e., social cohesion, informal social control and deviant peer affiliation) differed between social structures, that is, the identified longitudinal deprivation patterns. In line with previous studies, our findings demonstrated that the levels of social cohesion and informal social control were higher in lower deprivation patterns (Salvatore & Grundy, 2021; Sampson et al., 1997; Stafford et al., 2003; Steptoe & Feldman, 2001). Also, two types of deviant peers affiliation (i.e., burglars and perpetrators of physical abuse) were also higher in high deprivation patterns.

5.5.2.1 Social cohesion is a protective factor against CD behaviours development

Growing evidence has demonstrated that tight social cohesion in the neighbourhood diminishes CD behaviours development (Kingsbury et al., 2020; Silk et al., 2004). In such neighbourhoods, supportive adults are role models for children and adolescents, potentially attenuating their CD behaviours (Silk et al., 2004). Also, previous findings suggested that a high level of social cohesion can mitigate the detrimental effect of disadvantageous social structure in the neighbourhood, previous adverse life events and aggressive parenting styles on CD behaviours development (Kingsbury et al., 2020; O'Donnell & Barber, 2021; Silk et al., 2004). The present findings illustrated that, across all deprivation patterns, social cohesion (particularly friendly adults and young people) could mitigate CD behaviours development. Research on adolescents from 23 countries demonstrated that young people were less likely to engage in delinquency if the neighbourhood atmosphere is friendly (Binik et al., 2019).

5.5.2.2 Informal social control has a complex role in CD behaviours development

Sampson et al. (1997) suggested that informal social control depends on a tight-woven neighbourhood network and acts synergetically with social cohesion to form collective efficacy (Sampson, 2017). Previous studies often combined social cohesion and informal social control into a single measure: collective efficacy. However, a growing body of literature has shown that social structure (i.e., deprivation level) has relationships with social cohesion and informal social control in different ways (Rhineberger-Dunn & Carlson, 2009).

Our findings demonstrated that, unlike social cohesion, informal social control did not show an apparent protective effect against CD behaviours development. This result aligned with other research, illustrating that social cohesion and formal control do not behave the same way in the neighbourhood (Armstrong et al., 2015; Hart & Colavito, 2011; Reisig & Cancino, 2004). For instance, low informal social control did not predict neighbourhood violence as low social cohesion did (Armstrong et al., 2015). Also, high social cohesion was protective against neighbourhood burglary, but high informal social control did not have such a role (Reisig & Cancino, 2004). The present findings further showed that the indirect form of informal social control could potentially be a risk for CD behaviours development, particularly in the occasion, when adults reported seeing young people loitering.

In fact, a longitudinal study conducted in the US demonstrated that the frequency of police stops could predict future adolescent delinquency (Del Toro et al., 2019). The same study further suggested that psychological distress partially mediated this relationship (Del Toro et al., 2019). Our findings supported previous studies, showing that a friendly atmosphere (i.e., social cohesion) is more efficient than deterrence (i.e., informal social control) in contracting CD behaviours development.

5.5.2.3 Affiliation with deviant peers involved in burglary is a risk factor for CD behaviours development

Our result demonstrated that deviant peer affiliation with burglars was the most influential social mechanism risk factor in CD behaviours development. Deviant peer affiliation is one of the well-established risk factors for CD behaviours development (Lacourse et al., 2003; Patterson et al., 2000). Our results further indicated that, regardless of deprivation patterns, peers involved in property delinquency had the greatest influence on the CD behaviours development.

Price et al. (2019) compared different types of deviant peers and found that affiliation with peers involved in property delinquency (e.g., stealing, stealing from buildings, damaging property) predicts a high possibility of substance use in adulthood. Of interest, the same authors further demonstrated that, at the age between 12 and 14, the primary difference between the most severe deviant peers and other milder forms was property delinquency, not substance use (e.g., marijuana usage, hard drug usage). Our findings align with this observation, where we did not find a significant difference in drug offenders' affiliation across deprivation patterns.

The studies on the relationship between deprivation and drug usage had inconclusive results (Allison et al., 1999; Boardman et al., 2001; Ennett et al., 1997; Fauth et al., 2004; Ford & Beveridge, 2006; Giggs et al., 1989). For example, a Swedish study suggested a causal relationship between deprivation and drug abuse (Kendler et al., 2014). Nevertheless, another Swedish showed that the significant relationship between deprivation and drug abuse did not hold after controlling for familial covariates (Sariaslan et al., 2013). Of interest, a Norweigian study further showed that young people in affluent neighbourhoods the drug abuse the most (Pedersen & Bakken, 2016).

5.5.3 Crucial CD behaviours had less severity in less deprived social structure

Third, across deprivation networks, the CD behaviours that interacted the most with the social mechanism factors were identified. Of note, the most influential CD behaviours (i.e., bridge nodes) varied across deprivation patterns. Our results showed that the severity of the bridge CD behaviours increased with the level of deprivation patterns in a step-wise manner. In the deprived network, “bullying/threatened people” interacted the most with low social cohesion and high deviant peer affiliation. Adolescent bullying often takes place in a school setting, which also mirrors the larger neighbourhood context (Brewer et al., 2018; Smrekar & Bentley, 2011). For instance, hostile relationships among neighbours were correlated with higher bullying (bully-victims, Bowes et al., 2009). The same authors suggested that youths might learn such aggressive behaviours and impose them on their peers (Bowes et al., 2009).

On the contrary, less severe forms of CD behaviours, i.e., “lying" and “staying out after dark”, were bridge CD behaviours in the intermediate and the low deprivation patterns, respectively. Indeed, these CD behaviours are milder than “bullying and threatening others”. Still, they could be the initial signs of the CD behaviours development in intermediate and low deprivation patterns.

We also compared the interconnectivity between different deprivation networks. We found that the interconnectivity (i.e., global strength) was higher in the intermediate pattern (only deprived in crime and education) than in the deprived pattern (deprived in all domains). In the neighbourhood with the intermediate pattern, CD behaviours were impacted to a greater extent by the low level of social cohesion and high level of deviant peer affiliation. One may infer from the findings that policymakers should identify such neighbourhoods with intermediate patterns and initiate intervention (e.g., enhancing social cohesion). Intervention in such neighbourhoods can potentially prevent CD behaviours development with better efficiency.

5.5.4 Limitations

The present study results should be interpreted in light of its limitations. First, the time span of this study does not cover the entire adolescence but is constrained to the time window in which IMD data are comparable (from age 12.5 to 15.5). However, this time span does cover early adolescence, which is essential for CD behaviours development. Future research should use the ongoing IMD data collection and explore the deprivation influence throughout adolescence. Second, our study did not include the participants who had experienced the change in deprivation level due to their small number. Apart from the reason mentioned in the **5.5.3 Discussion**, that families often moved to a neighbourhood with similar characteristics, we suppose that a more extended study span with a longer IMD data window can capture more participants who had moved to a neighbourhood with different deprivation levels. Third, although the early year adversity is controlled in the present study, other factors might also be associated with the residence in a deprived neighbourhood. Fourth, we did not investigate the moderation by sex since further stratification of the participants may result in unstable network structures in the network analysis due to the small sample size in each network.

5.5.5 Conclusion

The study presented in this Chapter unveiled three longitudinal neighbourhood-level deprivation patterns: deprived, intermediate (solely deprived in education and crime) and low pattern. Across all three patterns, the most influential social mechanism risk factors were affiliation with deviant peers involved in burglary and indirect informal social control.

In contrast, across all three patterns, social cohesion factors played a protective role against the CD behaviours development. According to the deprivation pattern, the most influential CD behaviour varied in severity step-wise. In deprived neighbourhoods, bullying was the central influential CD behaviour. In the intermediate and low neighbourhood, lying and staying out after dark were the most influential CD behaviours.

CHAPTER 6: General discussion

6.1 Neighbourhood Mental Health Map

The aim of this thesis is to use a theoretical framework on urban neighbourhood mental health to guide three empirical studies. This framework is Neighbourhood Mental Health Map (**Figure 1.1**), adapted from the Settlement Health Map framework proposed by Barton (Barton & Grant, 2006; Barton, 2005). The Neighbourhood Mental Health Map is a people-centric framework in which people are positioned in the centre, surrounded by the social and physical environment in neighbourhoods and keep receiving influence from the outer environments. The layers in Neighbourhood Mental Health Map are not static but interact with each other. As Barton & Grant (2006) pointed out, neighbourhoods are more than independent artificial settlements but are integrated into the broader context (e.g., the natural world, Barton & Grant, 2006). Such a framework helps organise our thoughts regarding the relationship between people and neighbourhoods (Barton et al., 2021, p.36). Also, it provides a ground framework for validating other theories on public health, e.g., syndemic theory. In syndemic theory, different health problems co-occur and interact in a specific context. Neighbourhood Mental Health Map allows us to localise the architecture of context, whether it includes the layer of social mechanism, social structure or physical environment.

More specifically, in the studies presented in this thesis, we investigated the interactions between urban physical, social environments and people's mental health. In order to capture the complex topography of the urban physical and social environments, we used a wide range of geographical and census-level data (nighttime light emission data, satellite raw data, UKBUMP data and deprivation index, etc.). This yielded a multidimensional dataset, which required various multivariate methodologies (sCCA, msCCA, network analysis, LTA) to accommodate the multifacetedness of the information. These empirical findings (presented in

Chapter 3, **4**, and **5**) allowed readers to have a more comprehensive perspective on mental health in the urban neighbourhood context.

6.2 Syndemic in neighbourhood mental health

6.2.1 Syndemic methodological pipeline

Chapter 3 focused on a representative urban physical feature, nighttime light emission (NLE), and explored its relationships with other urban features (e.g., air pollution, deprivation) and mental, physical health problems. The study also aimed to implement the syndemic theory in the Neighbourhood Mental Health Map framework. Syndemic theory has three main general rules. First, two or more health problems co-occur in time or space; second, these health problems interact with each other in biological or social ways; and third, such interactions are facilitated by a context (Mendenhall et al., 2021; Singer, 1996; Tsai et al., 2017).

Various studies have been using different methods (from qualitative to quantitative) to evaluate the syndemic structure (Mendenhall & Singer, 2020). In recent years, researchers have moved from the ethnographical, qualitative approach to a more quantitative one (Mendenhall & Singer, 2020). Yet, with few exceptions, most studies used basic statistical methods to assess the syndemic structure quantitatively and could not capture the complexity of interactions in a syndemic structure (Bulled, 2021; Mendenhall & Singer, 2020). Moreover, most studies used the "syndemic count variable" approach (i.e., the number of health problems a participant reported) to evaluate syndemic structure (Tsai & Burns, 2015). For example, in one syndemic study, the authors found that the number of health problems is positively correlated with HIV infection and hence regarded as "syndemic" (Stall et al., 2003). Also, Parsons et al. (2012) used the "syndemic count variable" approach to test whether health problems (e.g., polydrug use, depression, sexual compulsivity) are syndemic factors of HIV infection and high-risk sexual practice. These studies sought to address two syndemic concepts: *co-occurrence* of health problems and the *context* in which health problems arise in clusters. However, such an approach failed to present the interconnectivity of *co-occurring* health problems, i.e., how intertwined the syndemic health problems are. Also, as Tsai & Burns (2015) criticised, such an approach did not address the *interaction* part of the syndemic theory because it does not test how these health problems interact with each other.

In **Chapter 3,** we proposed a syndemic methodological pipeline, including msCCA and network analysis, to account for the *co-occurrence*, *context*, and *interaction* concepts in syndemic theory. Using msCCA, we distilled the *co-occurring* mental and physical problems in the *context* of high NLE and other urban features. We modelled the environment-symptom network to address the interaction concept to assess the *interactions* between symptoms and the environment. Network analysis is an ideal tool for evaluating syndemic structure because it is designed to assess simultaneous interactions among various components (Choi et al., 2019).

6.2.2 Clustering of depression, obesity in the context of high NLE and other urban features

Integrating syndemic theory into the Neighbourhood Mental Health Map framework, our findings demonstrated a syndemic structure in high NLE areas. More specifically, depression and obesity and household poverty *co-occurred* in the *context* of a specific set of components in physical environments (e.g., air pollution, low green spaces) and social structures (e.g., economic deprivation, neighbourhood deprivation), characterised by high NLE. Then, we showed that the overall *interaction* between health problems and the environment (e.g., economic deprivation) is higher in the high NLE areas than in the low NLE areas.

High NLE is a prominent feature in urban neighbourhoods. Previous studies showed that high NLE was associated with diminished mental health, e.g., depression (Min & Min, 2018; Paksarian et al., 2020). Our findings echoed previous studies from various perspectives. From a comorbidity perspective, depression and obesity often co-occurred (Milaneschi et al., 2019). From a syndemic perspective, diminished mental and physical health are clustered in the context of deprivation, particularly in marginalised communities (Mendenhall et al., 2017). In addition, previous studies on NLE demonstrated that urban features, depression and obesity are tightly intertwined (Lai et al., 2020; Paksarian et al., 2020). As discussed in **Chapter 3**, the neuroanatomical structure of circadian rhythm and the chronic inflammation mechanism might account for the associations between NLE, depression and obesity (Fernandez et al., 2018; Hattar et al., 2006; Kalsbeek et al., 2011). Admittedly, the underlying biological mechanism and causality were beyond the scope of **Chapter 3**. However, the presented syndemic structure did imply some potential biological pathways and provided clues for future studies. Co-occurrence of depression and obesity is often coined as atypical depression, in which weight gain is one of the representative features. Since our results showed that waist circumference co-occurred with depression, the types of obesity or the location of the fat may play a crucial role in depression development. Waist circumference is a validated parameter for central obesity and accumulation of visceral fat (Ness-Abramof & Apovian, 2008). High visceral fat is associated with a range of chronic disorders, e.g., diabetes and cardiovascular diseases (Chait & den Hartigh, 2020; Després, 2007). Previous studies have shown that increased visceral fat is positively correlated with depression (Milaneschi et al., 2019; Vogelzangs et al., 2008; Zhao et al., 2011). Different from fat in other parts of the body, visceral fat releases pro-inflammatory cytokines (e.g., IL-6 and TNFα)(Kwon & Pessin, 2013). Increasing evidence has been demonstrating that elevated pro-inflammatory cytokines, in particular IL-6, are associated with depression (Dowlati et al., 2010; Himmerich et al., 2019; Howren et al., 2009; Köhler et al., 2017).

6.2.3 Interaction in the syndemic structure in urban neighbourhoods

The interaction was assessed at two levels. We compared the overall *interaction* (via global strength) among health problems and the environment between high vs low NLE areas. The overall interaction is greater in high NLE than in low NLE areas. We interpreted this finding as evidence of the higher synergy of health problems and environmental factors in the high NLE areas. Then, we assessed the *interaction* within the high NLE network. On the one hand, obesity interacted the most with social mechanism risks. On the other hand, household poverty, economic deprivation interact the most with mental, physical problems. Indeed, neighbourhoods with economic deprivation are often characterised by obesogenic environmental features, where foods rich in calories and low in nutrients are highly available. For example, the mean distance to fast food stores is shorter in deprived areas than in non-deprived areas; this fact makes unhealthy food more accessible to residents living in deprived neighbourhoods (Pearce et al., 2007). Recently, a French study further demonstrated a geographic overlap of obesity, depression and economic deprivation (Chauvet-Gelinier et al., 2019).

Admittedly, **Chapter 3** did not explore the causality of the associations between mental, physical symptoms or between environment and symptoms. Rather, the study presented a feasible quantitive approach to validate syndemic theory and implement the syndemic theory into the Neighbourhood Mental Health Map framework.

6.3 The data-driven approach in neighbourhood mental health

6.3.1 Satellite raw data as a tool to capture signatures in the physical environment

Chapter 4 aimed to understand how to identify physical environment signatures for specific mental health problems. In other words, **Chapter 4** focused on the associations between mental health and physical environment in the Neighbourhood Mental Health Map framework. To achieve this, we used satellite raw data as a tool to identify physical signatures (i.e., specific geographic patterns) of mental health problems. The usage of satellite raw data has two advantages. First, compared with ground-level data, it overcomes the administrative boundaries and temporal limitations. The satellite imagery keeps collecting information from the earth's surface and is a standardised measurement indifferent to administrative borders. Second, compared with ground-level data and satellite product data, the satellite raw data liberate researchers from focusing on a limited range of physical features (e.g., green space). More specifically, the physical signatures are derived from a wide range of satellite-detected wavelength bands. The identified physical signatures (i.e., the combination of wavelength bands) potentially contain information on physical features, which are yet to be identified and quantified as ground-level features or satellite product indexes.

Hence, by utilising the satellite raw data, we identified the physical signatures of depression, smoking, and overdrinking in **Chapter 4**. Since the linear combinations of satellite wavelength bands are abstract to interpret, we further employed the ground-level as an interpretation tool.

6.3.2 Depression, smoking behaviour in urban neighbourhoods

Our findings revealed that satellite-derived physical signatures for depression (one SWIR band and one NIR band) and smoking (two SWIR bands and one NIR band) were positively correlated with urban neighbourhood features. These urban neighbourhood features included less green space, more severe air pollution, a high density of roads and proximity to infrastructures. As for depression, our results support previous studies, showing that residential greenness had a protective effect against depression (Sarkar et al., 2018; Song et al., 2019). For example, Song et al. (2019) found that residents who belonged to the highest quartile of green exposure had the lowest odds to develop depression compared to the lowest quartile. Multiple theories have been proposed to explain the protective role of greenspaces (or nature) in depression. For instance, humans are evolutionarily inclined to nature (i.e., biophilia theory) and can restore concentration energy while in nature (i.e., attention restoration theory)(Kaplan, 1995; Kaplan & Kaplan, 1989; Kellert & Wilson, 1993). Attention restoration theory suggests that energy to concentration is often overly demanded and depleted in daily life, and exposure to nature (e.g., greenness) can restore the concentration ability. Our findings also suggested a positive correlation between depression and air pollution. Substances causing air pollution include particular matter (PM), carbon oxide (CO), carbon dioxide (CO_2), nitrogen (NOx) and sulfur oxides (SO_2, SO_3). Growing evidence has been showing the link between air pollution and depression (Lim et al., 2012; Szyszkowicz et al., 2009, 2016). Lim et al. (2012) found that increased pollutants, e.g., PM_{10}, NO_2, and O_3, are associated with higher depression in the elderly population. Szyszkowicz et al. (2009) further demonstrated that the concentration of certain air pollutants (e.g., CO, NO_2, SO_2, PM_{10}) is correlated with the daily emergency visit for depression. Different types of air pollutants influence the central nervous system in different ways. For example, CO disturbs the oxygen delivery ability in the brain (Szyszkowicz et al., 2009). PM_{10}, NO_2, and O_3 are regarded as pollutants imposing oxidation stress, which can contribute to depression development (Lim et al., 2012; Maes et al., 2011; Szyszkowicz et al., 2009).

Regarding smoking behaviour, our findings demonstrated that it had a similar satellite-derived physical signature as that of depression (**Table 4.3, Table S4.4**). So far, the studies on the relationship between the residential environment and smoking behaviour have inconclusive results (Roberts et al., 2017; Völzke et al., 2006; Taype-Rondan et al., 2017). However, it should be noted that most studies only employed urban-rural dichotomy design and did not further investigate the geographic features that correlated to smoking behaviours. In other words, our approach had a much higher resolution in two ways. First, we used satellite raw data to capture the physical signature of smoking behaviour directly. Second, we interpreted the satellite-derived physical signature with a wide range of ground-level features. This nuanced approach allowed us to delineate the geographic topography of smoking behaviour, which may be erroneously categorised into "urban" or "rural" in previous studies.

6.3.3 Depression-Smoking physical signature and its association with the brain

Satellite-derived physical signatures of depression and smoking shared the same urban features to a great extent. In the interpretation step, with the help of ground-level data, we found that both satellite-derived signatures connotate high air pollution, low green space, shorter distance to a range of facilities (i.e., education, healthcare and services) and high density of streets (**Chapter 4**, **Table 4.3**). In other words, both satellite-derived signatures of depression and smoking characterised an urban environment. As we further investigated the brain signatures correlated to depression/smoking and the corresponding satellite-derived signatures, we found that their brain signatures were similar too.

In general, this shared brain signature is particularly located in the cerebellum. Our results illustrated that the reduction in the volume of posterior regions in the cerebellum (crus I, lobule VI, VIIB, VIIIA and VIIIB) was associated with both the depression physical signature and the smoking physical signature. The cerebellum is essential in motor function coordination and high-level cognitive function (Buckner et al., 2011). It has been shown that high-level cognitive function is involved within the posterior part of the cerebellum (Buckner et al., 2011; Sang et al., 2012). Both depression and smoking behaviour have been reported correlated to reduction of the grey matter of the posterior cerebellum (Grieve et al., 2013; Kühn et al., 2012). Our results supported previous evidence and showed that reduction of grey matter volume in these brain regions is correlated to urban physical signatures.

6.3.4 Overdrinking in suburban neighbourhoods

Our results implied that overdrinking is associated with suburban neighbourhood features and depends on deprivation level. For example, an American study reported that the odds of overdrinking were higher for residents living in the least deprived regions (Pollack et al., 2005). Of note, associations between the alcohol intake/overdrinking physical signatures and their interpreted geographic features are much lower than the correlation between depression/smoking physical signatures and their corresponding interpreted geographic features. This implies that, apart from the geographic categories available in the UKBB, there are other geographic characteristics that contribute to the overdrinking satellite-derived physical signature.

After interpreting with ground-level data, the overdrinking satellite-derived physical signature characterised a neighbourhood with less air pollution, more water, less deprivation, less unused land and less density of factories. These geographic characteristics do not fit well in the urban/rural dichotomy. Therefore, in **Chapter 4**, we used the term "suburban" to summarise this finding. Indeed, the relationship between alcohol intake behaviour and geographic location is complicated (Dixon & Chartier, 2016). Previous studies on overdrinking using urban/rural dichotomy had inconclusive findings (Donath et al., 2011; Grant, 1997).

6.3.5 Overdrinking physical signature and its brain feature

Alcohol intake significantly impacts brain structure and is associated with global brain volume reduction (Harper & Kril, 1985; Jernigan et al., 1991). **Chapter 4** revealed that both alcohol intake and overdrinking behaviour were correlated with the reduction of GMV in brain stem, right cuneal cortex, right lateral occipital cortex (superior division), left occipital pole, right planum polare, left precuneous cortex and thalamus. Previous findings showed that excessive alcohol consumption is associated with GMV reduction in both cortical and subcortical regions, e.g., frontal, temporal, insular gyrus, thalamus, putamen, accumbens and hippocampus (Durazzo et al., 2011; Grodin et al., 2013; Jernigan et al., 1991; Mechtcheriakov et al., 2007; Rando et al., 2011; Shim et al., 2019; van Holst et al., 2012).

Of note, our study demonstrated a decreased volume of the thalamus in both alcohol intake and overdrinking. Thalamus is the central region of the two most affected brain networks in alcoholism: Pepez circuit and the frontocerebellar brain network. Reduced volume of the thalamus is frequent in alcohol abusers and is one of the main findings in Korsakoff syndrome. Apart from being in line with previous evidence, our findings further indicated that the GVM reduction in certain areas and volume shrinkage of the thalamus are associated with the physical signature which depicted a suburban environment.

6.4 Social environment in neighbourhood mental health

6.4.1 Social structure in neighbourhood mental health

Chapter 5 focused on the interactions between social environment and peoples' mental health in the Neighbourhood Mental Health Map. More specifically, **Chapter 5** aimed to investigate how conduct disorder (CD) behaviours interact with social mechanisms in the context of social structures (i.e., different deprivation patterns). The study demonstrated three types of social structure, characterised by the longitudinal deprivation patterns (i.e., constant deprived, intermediate and low). We found that very few participants have experienced a change in the social structure (i.e., deprivation pattern) over time. There are two possible explanations for this finding. First, it is plausible that the majority of families stayed at their original address throughout these three years, hence exposed to the same social structure. Second, families who moved might move to neighbourhoods with the same social structure (i.e., deprivation pattern). Indeed, previous studies from the UK and USA illustrated that mobility between deprived and non-deprived neighbourhoods is unlikely (Flouri et al., 2013; Sharkey, 2012). If the people did move, they tended to move to communities with similar characteristics to their previous neighbourhoods (Sharkey, 2012). Due to the small number of participants who experienced a change in deprivation patterns, we were unable to assess how this change was associated with the CD development trajectories. Previous studies using results from Moving to Opportunity (MTO) tried to answer this question (Sampson, 2008). In MTO, families below the poverty line were offered the opportunity to move to a less deprived neighbourhood. The assignment to the experimental group was random, making the project ideal for evaluating the effect of change in social structure. However, the outcomes regarding mental health were complex. For example, after relocation to less deprived neighbourhoods, boys showed an improvement in mood problems (Leventhal & Brooks-Gunn, 2003). On the other hand, no such improvement was seen in CD behaviours both in boys and girls (Leventhal & Brooks-Gunn, 2003).

As illustrated, the MTO project only dealt with an “upward move” (i.e., from deprived to less deprived neighbourhoods). Future studies can either lengthen the study time span or combine other cohorts, to gain more insight into the population who has experienced a change in social structure.

6.4.2 Social mechanism is weakened in detrimental social structure

In the Neighbourhood Mental Health Map, the social mechanism forms the inner layer of the social environment. This aligns with the empirical studies that showed social mechanisms mediate social structure and individuals’ outcomes (Sampson et al., 1997). Our findings illustrated that social mechanisms are better in social structure characterised with low deprivation features. For example, social cohesion and informal social control levels were lower in the worse social structure (Salvatore & Grundy, 2021; Sampson et al., 1997; Stafford et al., 2003; Steptoe & Feldman et al., 2001). Also, deviant peer affiliation (with burglars and perpetrators of physical abuse) was higher in the social structure characterised by high deprivation. This finding indicated that in neighbourhoods with social structural defects (e.g., low neighbourhood-level SES, low neighbourhood-level education, high crime rate), the strength of social mechanisms deteriorates.

6.4.3 Interactions between mental health and social mechanism in different social structures

Social mechanisms (i.e., social cohesion, informal social control and deviant peer affiliation) played a mediating role between social structure and individual outcomes (Sampson et al., 1997). Therefore, it is interesting to investigate how individual outcomes (e.g., CD behaviours in adolescence) interact with social mechanisms in different social structures (i.e., deprivation patterns). Our findings demonstrated that, in all kinds of social structures, social cohesion (particularly friendly adults and young people in the neighbourhood) mitigates CD behaviours development. Indeed, previous studies showed that tight social cohesion in the neighbourhood diminishes CD behaviours development (Kingsbury et al., 2020). Supportive adults in neighbourhoods can serve as role models for young people, and mitigate their CD behaviours (Silk et al., 2004). Another international study showed that the delinquency of children and adolescents is lower in neighbourhoods with better social mechanism (Binik et al., 2019).

In contrast to social cohesion, informal social control appeared to have a complicated role in CD behaviours development. Indeed, our findings showed that informal social control was higher in less deprived social structures. However, our results also questioned its benefit of protecting young people from CD behaviours development because informal social control with police engagement (when youth loitering) facilitates the CD behaviours development. Such finding echoed an American longitudinal study showing that deterrence with police stops predicted future adolescent crime (Del Toro et al., 2019). This finding also questioned the rationale to combine social cohesion and informal social control under the same umbrella term, collective efficacy, as suggested by Sampson et al. (1997). Indeed, growing evidence has shown that social cohesion and informal social control should be assessed separately because they have different roles and might lead to different outcomes in neighbourhoods (Armstrong et al., 2015; Hart & Colavito, 2011; Reisig & Cancino, 2004).

The social mechanism presented in **Chapter 5** also included deviant peer affiliation. Our result illustrated that deviant peer affiliation with burglars was the most influential social mechanism risk factor for CD behaviours development. Although previous studies have established the link between deviant peer affiliation and CD behaviour (Lacourse et al., 2003; Patterson et al., 2000), very few studies further differentiated the types of deviant peers and assessed their roles in CD behaviours development. To our knowledge, only one study found that affiliation with deviant peers engaged with property crime predicts substance use in adulthood (Price et al., 2019).

6.4.4 Influential CD symptoms are different in different social structures

The most influential CD behaviours (i.e., bridge CD behaviours) were different across social structures. Our results demonstrated that the severity of the bridge CD behaviours increased with the deprivation level of social structure in a step-wise manner.

In the social structure characterised by deprived features, "bullying/threatened people" had the highest interaction with the social mechanism. For young people, bullying often occurs in a school setting, reflecting the larger neighbourhood context (Brewer et al., 2018; Smrekar & Bentley, 2011). It has been shown that young people might learn from their aggressive neighbours and repeat such behaviours to their peers (Bowes et al., 2009). In contrast, our findings revealed that milder forms of CD behaviours, i.e., "lying" and "staying out after dark", were influential CD behaviours (i.e., bridge nodes) in the social structures with intermediate and low deprivation features, respectively.

6.5 Limitations and outlooks

The findings in this thesis should be interpreted in light of the limitations. First, the datasets (i.e., UKBB, ALSPAC) used in these three projects are UK-based. The results might be comparable in countries with similar political-economic status as the UK, where the urbanisation rate is relatively stable. It is unknown whether these findings can be transferable to developing countries, especially where drastic urbanisation and change in land use are taking place at a fast rate (e.g., in African cities). Second, although the projects benefit from the large sample size and thorough measurements, readers should bear in mind that the ethnic background of the demographics is primarily White. Indeed, the study samples were intentionally confined to Whites in **Chapter 3** and **Chapter 4** to minimise the ethnic difference in the circadian rhythm and potential heritable preference for residential locations (Cronqvist et al., 2014; Eastman et al., 2015; Egan et al., 2017; Malone et al., 2016). Also, datasets (e.g., ALSPAC) can contain primarily White participants. The first and second limitations imply that future studies can employ datasets collected in countries with different ethnic backgrounds (e.g., China Kadoorie Biobank). Third, the Neighbourhood Mental Health Map does not empathise with the temporal dimension. The temporal dimension was only included in **Chapter 5**. However, due to the limitation of the sample, we could only select the participants exposed to the same social structure across time. Future studies should implement the temporal dimension. That is, the interactions between layers in the Neighbourhood Mental Health Map can change over time.

6.6 Conclusions

The present thesis presented three empirical studies on neighbourhood mental health and implemented them into a Neighbourhood Mental Health Map framework. **Chapter 3** and **Chapter 4** focused on the interactions between the physical environment and mental health. In **Chapter 3**, we identified the syndemic structure of depression, obesity and poverty in urban neighbourhoods, characterised by high nighttime light emission. In **Chapter 4**, we presented the usage of satellite raw data to delineate the associations between mental health and the physical environment. We demonstrated that the satellite-derived physical signatures of depression and smoking had an urban topography, whereas that of overdrinking had a suburban topography. Also, we identified the brain signatures correlated with the mental problems and the associated satellite-derived physical signatures. **Chapter 5** focused on the interaction between the social environment and mental health. In **Chapter 5**, we demonstrated that conduct disorder was higher and social mechanism was weaker as social structure worsened (i.e., deprivation level increased). Among different social mechanisms, deviant peer affiliation contributed to conduct disorder development. On the other hand, social cohesion has a protective role for young people, preventing them from developing conduct disorder behaviours.

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Figures

Tables

Appendix (Supplementary material)

Table S3.1 Urban feature categories and measures

Categories	Measures
Traffic	Close_to_major_road
	Inverse_distance_nearest_major_road
	Sum_of_road_length_major_roads_within_100m
	Traffic_intensity_nearest_road
Air pollution	Nitrogen_dioxide_air_pollution_2010
	Nitrogen_oxides_air_pollution_2010
	PM2_5_air_pollution_2010
	PM10_air_pollution_2010
Sound pollution	Average_daytime_sound_level_of_noise_pollution
	Average_evening_sound_level_of_noise_pollution
	Average_night_time_sound_level_of_noise_pollution
Green space	Green space_percentage_buffer_1000m
	Natural_environment_percentage_buffer_1000m
Deprivation_income_employment_education	IMD_score
	Income_score
	Employment_score
	Education_skills_and_training_score
	Children_Young_People_Sub_domain_score
	IDACI_score
Deprivation_crime_living_env_housing	Crime_and_disorder_score
	Living_environment_score
	Indoors_Sub_domain_Score

	Outdoors_Sub_domain_Score
	Wider_Barriers_Sub_domain_Score
Slope	Slope500m_Mean
	Slope500m_Maximum
	Slope500m_STD
Distance_education	ND_CE01_College
	ND_CE02_Childrens_Nursery_Creche
	ND_CE03_Preparatory_First_Primary_Infant_Junior_M
	ND_CE04_Secondary_High_School
	ND_CE05_University
Distance_factory	ND_CI01_Factory_Manufacturing
	ND_CI02_Mineral_Ore_Working_Quarry_Mine
	ND_CI03_Workshop_Light_Industrial
	ND_CI04_Warehouse_Store_Storage_Depot
Distance_community	ND_CC04_Public_Village_Hall_Other_Community_Facility
	ND_CL03_Library
	ND_CL07_Cinema_Conf_Exhib_Centre_Theatre_Concert_Hall
	ND_ZW_Places_of_Worship
Distance_healthcare	ND_CM01_Dentist
	ND_CM02_GP_Practice_Surgery_Clinic
	ND_CM03_Hospital_Hospice
Distance_services	ND_CC12_Job_Centre
	ND_CO01GV_Central_Government_Service
	ND_CO01LG_Local_Government_Service
	ND_CR01_Bank_Financial_Service
	ND_CR02_Retail_Service_Agent

	ND_CR02PO_Post_Office
Distance_waste_and_energy	ND_CU02_Landfill
	ND_CU03_Power_Station_Energy_Production
	ND_CU07_Water_Waste_Water_Sewage_Treatment_Works
	ND_Recycling_Recycling
Distance_transport	ND_CT03_Parking_Park_and_Ride_Site
	ND_CT08_Station_Interchange_Terminal_Halt
Distance_emergency	ND_CX01_Police_Transport_Police_Station
	ND_CX02_Fire_Station
	ND_CX03_Ambulance_Station
Distance_food	ND_CR06_Public_House_Bar_Night_Club
	ND_CR07_Restaurant_Cafeteria
	ND_CR10_Fast_Food_Outlet_Takeaway
Density_agricultural	Den_CA01_Farm_Non_Residential_Associated_Building
	Den_CA02_Fishery
	Den_CA03_Horticulture
Density_education	Den_CE_Education
	Den_CE02_Childrens_Nursery_Creche
	Den_CE03_Preparatory_First_Primary_Infant_Junior_Middle_School
	Den_CE03NP_Non_State_Primary_Preparatory_School
	Den_CE04_Secondary_High_School
	Den_CE05_University
Density_accommodation	Den_CH01_Boarding_Guest_House_Bed_And_Breakfast_Youth_Hostel
	Den_CH02_Holiday_Let_Accommodation_Short_Term_Let
	Den_CH03_Hotel_Motel
Density_factory	Den_CI01_Factory_Manufacturing

	Den_CI03_Workshop_Light_Industrial
	Den_CI04_Warehouse_Store_Storage_Depot
Density_physical_activity1	Den_CL06_Indoor_Outdoor_Leisure_Sporting_Activity_Centre
	Den_CL06CK_Cricket_Facility
	Den_CL06QS_Racquet_Sports_Facility
	Den_CL06WA_Water_Sports_Facility
Density_physical_activity2	Den_CL06FB_Football_Facility
	Den_CL06LS_Activity_Leisure_Sports_Centre
	Den_CL06RF_Rugby_Facility
Density_healthcare	Den_CM_Medical
	Den_CM01_Dentist
	Den_CM02_General_Practice_Surgery_Clinic
	Den_CM02HC_Health_Centre
	Den_CM02HL_Health_Care_Services
	Den_CM05_Prof_Medical_Service_Assessment_Developm_Services
Density_hospital	Den_CM03_Hospital_Hospice
	Den_CM03HI_Hospice
	Den_CM03HP_Hospital
	Den_CM04_Medical_Testing_Research_Laboratory
Density_animal_centre	Den_CN02_Animal_Services_Animal_Quarantining
	Den_CN04_Vet_Animal_Medical_Treatment
Density_food	Den_CR06_Public_House_Bar_Nightclub
	Den_CR07_Restaurant_Cafeteria
	Den_CR09_Other_Licensed_Premise_Vendor
	Den_CR10_Fast_Food_Outlet_Takeaway_Hot_Cold
Density_emergency	Den_CX01_Police_Transport_Police_Station

	Den_CX02_Fire_Station
	Den_CX03_Ambulance_Station
Density_street	Den_CZ01_Advertising_Hoarding
	Den_CR11_Automated_Teller_Machine_ATM
	Den_CU11_Telephone_Box
	Den_Bstops_Density_of_bus_stops
Density_maintained_areas	Den_LM01_Landscaped_Roundabout
	Den_LM02_Verge_Central_Reservation
	Den_LM03_Maintained_Amenity_Land
	Den_LM04_Maintained_Surfaced_Area
Density_park	Den_LM_Amenity_Open_areas_not_attracting_visitors
	Den_LP01_Public_Park_Garden
	Den_LP02_Public_Open_Space_Nature_Reserve
	Den_LP03_Playground
Density_unused_land	Den_LL_Allotment
	Den_LU01_Vacant_Derelict_Land
Density_water	Water_percentage_buffer_1000m
	Den_LW01_Lake_Reservoir
	Den_LW02_Named_Pond
Density_military	Den_M_Military
	Den_MA_Army
Density_residence_general	Den_R_Residential
	Den_RB_Ancillary_Building
	Den_RC01_Car_Park_Space
	Den_RD_Dwelling
Density_residence_HMO	Den_RH01_HMO_Parent

	Den_RH02_HMO_Bedsit_Other_Non_Self_Contained_Accommodation
	Den_RH03_HMO_Not_Further_Divided
Density_residence_detached	Den_RD02_Detached
	Den_RD03_Semi_Detached
	Den_RD04_Terraced
	Den_RD06_Self_Contained_Flat_Includes_Maisonette_Apartment
Density_residence_communal	Den_RI01_Care_Nursing_Home
	Den_RI02_Communal_Residence
	Den_RI03_Residential_Education
Density_monument	Den_ZM01_Obelisk_Milestone_Standing_Stone
	Den_ZM02_Memorial_Market_Cross
	Den_ZM03_Statue
	Den_ZM05_Other_Structure_Art_Display_Cascade_Fountain_Windmill
Density_underground_feature	Den_Z_Object_of_Interest
	Den_ZS_Stately_Home
	Den_ZU_Underground_Feature
	Den_ZV_Other
Density_church	Den_ZW_Place_Of_Worship
	Den_ZW99CH_Church
	Den_ZW99MQ_Mosque
	Den_ZW99TP_Temple
Density_transport	Den_CT_Transport
	Den_CT02_Bus_Shelter
	Den_CT07_Railway_Asset
	Den_CT08_Station_Terminal_Halt_Bus_Coach_Railway_Station
	Den_CT09_Transport_Track_Way

	Den_CT10_Vehicle_Storage
	Den_CT11_Transport_Related_Infrastructure
Density_waste_and_energy	Den_CC10_Recycling_Site
	Den_CU_Utility
	Den_CU01_Electricity_Sub_Station
	Den_CU06_Telecommunication
Density_community	Den_CC04_Community_Facility_Youth_Recreat_Social_Club
	Den_CC07_Church_Hall_Religious_Meeting_Place_Hall
	Den_CL01_Amusements_Leisure_Pier
	Den_CL03_Library
	Den_CL04_Museum_Gallery
	Den_CL07_Cinema_Conference_Exhib_Centre_Theatre_Concert_Hall
	Den_CL10_Licensed_Private_Members_Club_Recreational_Social_Club
Density_services	Den_CC05_Public_Convenience
	Den_CO01_Office_Work_studio
	Den_CR01_Bank_Financial_Service
	Den_CR02_Retail_Service_Agent_Post_Office
	Den_CR08_Shop_Showroom_Garden_Centre

Table S3.2 Wellbeing factors

Depression and anxiety symptoms

Acronym	Name of the measure	Question
Dpr	frequency of depressed mood in the last 2 weeks	Over the past two weeks, how often have you felt down, depressed, or hopeless?
Dis	frequency of unenthusiasm/disinterest in the last 2 weeks	Over the past two weeks, how often have you had little interest or pleasure in doing things?"

Ten	frequency of tenseness/restlessness in the last 2 weeks	Over the past two weeks, how often have you felt tense, fidgety, or restless?"
Trd	frequency of tiredness/lethargy in the last 2 weeks	Over the past two weeks, how often have you felt tired or had little energy?
Irr	irritability	Are you an irritable person?
Nrv	nervous feelings	Would you call yourself a nervous person?
Wor	worrier / anxious feelings	Are you a worrier?
Tns	tense / 'highly strung'	Would you call yourself tense or 'highly strung'?"
Emb	worry too long after the embarrassment	Do you worry too long after an embarrassing experience?

Obesity measures

Acronym	Name of the variable	Question
BMI	BMI	BMI value here is constructed from height and weight measured during the initial Assessment Centre visit.
Wst	Waist Circumference	Waist circumference
Fat	Body fat percentage	Body composition estimation by impedance measurement.
Wei	Weight	Weight was measured by a variety of means during the initial Assessment Centre visit

Physical Activity

Acronym	Name of the variable	Question
Vig	Number of days/week of vigorous physical activity 10+ minutes	In a typical WEEK, on how many days did you walk for at least 10 minutes at a time? (Include walking that you do at work, traveling to and from work, and for sport or leisure)
Mod	Number of days/week of moderate physical activity 10+ minutes	In a typical WEEK, on how many days did you do 10 minutes or more of moderate physical activities like carrying light loads, cycling at a normal pace?
Wit	Number of days/week walked 10+ minutes	In a typical WEEK, how many days did you do 10 minutes or more of vigorous physical activity? (These are activities that make you sweat or breathe hard such as fast cycling, aerobics, heavy lifting)

Sleep pattern

Acronym	Name of the variable	Question
Ins	Sleeplessness / insomnia	"Do you have trouble falling asleep at night or do you wake up in the middle of the night?"
Gup	Getting up in the morning	On an average day, how easy do you find getting up in the morning?
Nap	Nap during day	Do you have a nap during the day?
Snr	Snoring	Does your partner or a close relative or friend complain about your snoring?
Doz	Daytime dozing/sleeping (narcolepsy)	How likely are you to doze off or fall asleep during the daytime when you don't mean to? (e.g. when working, reading or driving)
Sdu	Sleep duration	About how many hours sleep do you get in every 24 hours? (please include naps)

Household poverty

Acronym	Name of the variable	Question
PV	Household poverty	Inversely coded variable based on yearly income before tax (income1 less than £18,000; income2: £18,000 to £29,999, income3: £30,000 to £51,999, income4: £52,000 to £100,000, income5: greater than £100,000)

Table S4.1. Depression sum score

Index	Name of the variable	Question
2050	frequency of depressed mood in last 2 weeks	Over the past two weeks, how often have you felt down, depressed or hopeless?
2060	frequency of unenthusiasm / disinterest in last 2 weeks	Over the past two weeks, how often have you had little interest or pleasure in doing things?”
2070	frequency of tenseness / restlessness in last 2 weeks	Over the past two weeks, how often have you felt tense, fidgety or restless?”
2080	frequency of tiredness / lethargy in last 2 weeks	Over the past two weeks, how often have you felt tired or had little energy?

Table S4.2. Anxiety sum score

Index	Name of the variable	Question
1940	irritability	Are you an irritable person?
1970	nervous feelings	Would you call yourself a nervous person?
1980	worrier / anxious feelings	Are you a worrier?
1990	tense / 'highly strung'	Would you call yourself tense or ‘highly strung’?”
2000	worry too long after embarrassment	Do you worry too long after an embarrassing experience?
2010	suffering from ‘nerves’	Do you suffer from ‘nerves’?

Table S4.3 Correlation between mental problems

	Depression	Anxiety	Smoking	Alcohol Frequency	Alcohol Amount	Overdrinking
depression		0.4362**	0.1053**	-0.0975**	-0.0262**	-0.0545**
anxiety			0.0072*	-0.0364**	-0.0317**	-0.0400**
smoking				-0.0064*	0.0956**	0.0436**
alcohol frequency					0.6582**	0.6815**
alcohol amount						0.7104**
overdrinking						

Corrected p value (p<0.01, p<0.001 **)*

Table S4.4 Correlation between identified satellited-derived physical signatures

	Depression	Anxiety	Smoking	Alcohol Amount	Overdrinking
Depression	1	0.7244**	0.9498**	-0.4426**	-0.6581**
Smoking			1	-0.1928**	-0.4426**
Alcohol Amount				1	0.9463**
Overdrinking					1

*Corrected p value (p<0.001**)*

Table S4.5. Brain Signature correlated to physical depression signature and depression score.

Index	Brain Region	Loadings
15	Right Cerebellum crus I	-0.3427
36	Left inferior frontal gyrus pars opercularis	-0.3783
50	Left juxtapositional lobule cortex	-0.3570
58	Left middle frontal gyrus	-0.3111
120	Left cerebellum VI	-0.3161
122	Left cerebellum VIIIa	-0.3390
123	Right cerebellum VIIIa	-0.4487
127	Right cerebellum VIIb	-0.3147

$r_{training}$=0.0492 (0.0415,0.0374,0.0687), $p_{training}$=0.002; r_{test}= 0.0366 (0.0319,0.0309,0.0469), p_{test}=0.024

Table S4.6. Brain Signature correlated to physical smoking signature and smoking score.

Index	Brain Region	Loadings
2	Right amygdala	-0.3063
15	Right crus I cerebellum	-0.2952
50	Left juxtapositional lobule cortex	-0.2747
67	Right occipital fusiform gyrus	-0.2850
89	Right precuneous cortex	-0.2985
120	Left cerebellum VI	-0.3096
122	Left cerebellum VIIIa	-0.3463

123	Right cerebellum VIIIa	-0.3726
125	Right cerebellum VIIIb	-0.2632
126	Left cerebellum VIIb	-0.2844
127	Right cerebellum VIIb	-0.2615

$r_{training}$=0.0598 (0.0443,0.0646,0.0705), $p_{training}$<0.001; r_{test}= 0.0597 (0.0728, 0.0426,0.0635), p_{test}<0.001

Table S4.7. Brain Signature correlated to physical alcohol amount signature and alcohol amount.

Index	Brain Region	Loading
5	Brain Stem	-0.3100
19	Right Cuneal Cortex	-0.2406
22	Left Frontal Operculum Cortex	-0.2390
26	Left Frontal Pole	-0.2386
47	Right Insular Cortex	-0.2468
55	Right Lateral Occipital Cortex (superior division)	-0.2591
68	Left Occipital Pole	-0.2847
81	Right Planum Polare	-0.3039
88	Left Precuneous Cortex	-0.2814
89	Right Precuneous Cortex	-0.2754
116	Left Thalamus	-0.2506
117	Right Thalamus	-0.2436
152	Volume of left thalamus	-0.2551
153	Volume of right thalamus	-0.2971

$r_{training}$= 0.0756 (0.0239,0.1338,0.0692), $p_{training}$<0.001; r_{test}= 0.0605 (0.0526,0.0995,0.0294), p_{test}=0.001

Table S4.8 Brain Signature correlated to physical overdrinking signature and overdrinking.

Index	**Brain Region**	**Loading**
5	Brain Stem	-0.3686
19	Right Cuneal Cortex	-0.2777
55	Right Lateral Occipital Cortex (superior division)	-0.2522
68	Left Occipital Pole	-0.3466
81	Right Planum Polare	-0.3193
88	Left Precuneous Cortex	-0.2913
90	Left Putamen	-0.2660
116	Left Thalamus	-0.3201
117	Right Thalamus	-0.3046
152	Volume of left thalamus	-0.2598
153	Volume of right thalamus	-0.2880

$r_{training}$= 0.0614 (0.0466, 0.0756,0.0619), $p_{training}$<0.001; r_{test}= 0.0515 (0.0593,0.0686,0.0266), p_{test}<0.001

Figure 4.7 was created using MRIcron.

The cerebellum parts are based on SUIT atlas.

Diedrichsen, J. (2006). A spatially unbiased atlas template of the human cerebellum. Neuroimage, 33, 1, p. 127-138. pdf format

Diedrichsen, J., Balsters, J. H., Flavell, J., Cussans, E., & Ramnani, N. (2009). A probabilistic atlas of the human cerebellum. Neuroimage. pdf format

Diedrichsen, J., Maderwald, S., Kuper, M., Thurling, M., Rabe, K., Gizewski, E. R., et al. (2011). Imaging the deep cerebellar nuclei: A probabilistic atlas and normalisation procedure. Neuroimage.pdf format

Diedrichsen, J. & Zotow, E. (2015). Surface-based display of volume-averaged cerebellar data. PLoS One, 7, e0133402.

Table S5.1 AIC, BIC and SABIC in three-class and four-class LTA models on the whole sample with IMD measures

Information Criteria \ LTA model	Three-class model	Four-class model
AIC	384930.259	366089.280
BIC	385534.738	366927.994
SABIC	385280.505	366575.246

Table S5.2. The latent transition probabilities based on the estimated model

Time1/Time2	Deprived	Intermediate	Low
Deprived	0.954	0.032	0.014
Intermediate	0.015	0.946	0.039
Low	0.002	0.020	0.978

Table S5.3. The latent transition patterns proportion in the ALSPAC sample

Latent Class (Time1->Time2)	N	%
Deprived->Deprived	3,090	21.870
Deprived->Intermediate	111	0.786
Deprived->Low	42	0.297
Intermediate->Deprived	71	0.503
Intermediate->Intermediate	5,069	35.877
Intermediate->Low	189	1.338
Low->Deprived	13	0.092
Low->Intermediate	79	0.559
Low->Low	5,465	38.679

Table S5.4. The difference in CD and environmental risk factors between deprivation patterns

		ANCOVA	**Deprived-Intermediate**	**Intermediate-Low**	**Deprived-Low**
Conduct disorder		F=6.08379261 p=0.00289971	t= 2.56 ,p= 0.0348	t= 3.415 ,p= 0.003	t= 4.511 ,p= 6e-04
Social cohesion		F= 4.56368147 p=0.01079892	t= -2.623, p= 0.0333	t= -2.513, p= 0.0393	t= -4.422, p= 3e-04
Direct informal social control (move on)		F=44.33281619 p=0.00009999	t= -7.189, p= 3e-04	t= -4.17, p= 6e-04	t= -10.057, p= 3e-04
Indirect informal social control (call police)		F=7.72930702 p=0.00049995	t= -3.581 ,p= 0.0021	t= -1.501 ,p= 0.414	t= -4.652 ,p= 6e-04
Friends involved in	Burglary	F=12.86362226 p=0.00009999	t= 3.212 ,p= 0.009	t= 1.023 ,p= 0.9203	t= 3.786 ,p= 0.003
	Drug offence	F=2.52097587 p=0.07719228	t= 2.437 ,p= 0.0489	t= 1.186 ,p= 0.7106	t= 3.284 ,p= 0.0018
	Perpetration of physical abuse	F=5.52133152 p=0.00449955	t= 3.136 ,p= 0.0093	t= 1.174 ,p= 0.7202	t= 3.934 ,p= 3e-04

Exploratory factor analysis summarized nine deviant peer items into three aspects: friends involved in burglary, drug offence, and perpetration of physical abuse

Nine deviant peer items were summarized into three factors using exploratory factor analysis. Three items, “friends breaking into a car”, “friends breaking into a house”, and “friends riding a stolen car”, were summarized into the factor “friends involved in burglary”. Two items, “friends using illegal drugs”, and “friends selling drugs”, were summarized into the factor “Friends involved in drug offence”. Four items, “friends carrying knives or weapons”, “friends hitting (kicked, punched)”, “friends attacking with intention (picked on someone)” and “friends hurting animals” were summarized into the factor “friends involved in physical abuse” (**Figure S5.1**). The Tucker Lewis Index of factoring reliability was 0.979 and the RMSEA index was 0.0334.

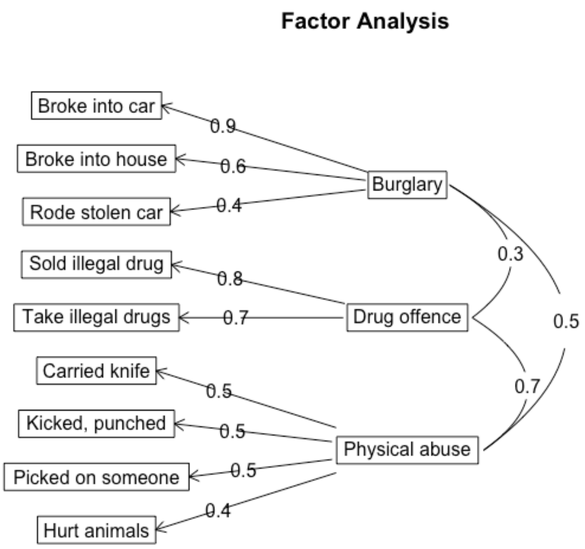


Figure S5.1. Exploratory factor analysis of deviant peer items. Nine deviant peer items were summarized into three factors: friends involved in “burglary”, “drug offence” and perpetration of “physical abuse”.

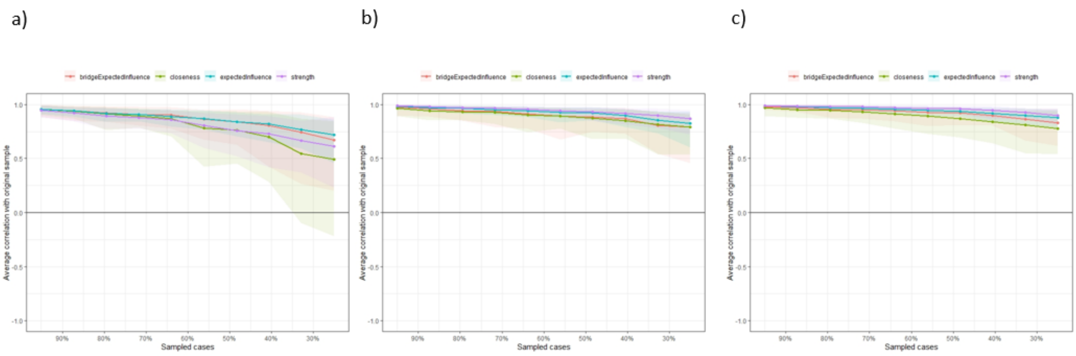


Figure S5.2. Stability in deprived (a), intermediate (b) and low (c) networks.

Tables of acronyms

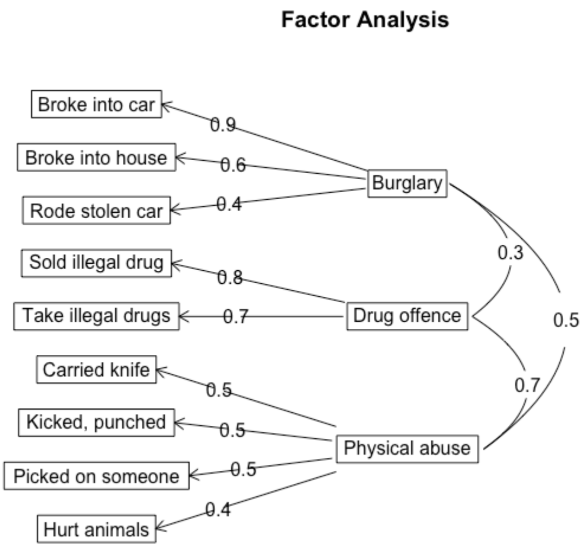
Conduct disorder

Index	Acronyms	Items
fh9558	Lie	"told lies"
fh9560	Fgh	"started fights other than with siblings"
fh9562	Bll	"bullied/threatened people"
fh9564	Drk	"stayed out after dark much later than supposed to"
fh9566	Stl	"stolen from house/others/shops"
fh9568	Awy	"run away from home more than once or stayed away all night without permission"
fh9570	Trn	"played truant"

Deviant peers

Index	Items
fh8342	EY2390: Number of YPs friends that **took** illegal, **drugs** during the last year : TF3
fh8351	EY2410: Some of YPs friends kicked/punched/attacked someone with the intention of really hurting them, during the last year : TF3
fh8353	EY2430: Some of YPs friends hit or picked on someone because of their

	race or skin colour, during the last year : TF3
fh8355	EY2450: Some of YPs friends **broke** into a house or building to steal something, during the last year : TF3
fh8356	EY2460: Some of YPs friends **broke** into a car/van to steal something, during the last year : TF3
fh8360	EY2500: Some of YPs friends **rode** in a stolen car/van/motorbike, during the last year : TF3
fh8364	EY2540: Some of YPs friends carried a knife or other weapon for protection or in case it was needed in a fight, during the last year : TF3
fh8365	EY2550: Some of YPs friends sold an illegal drug to someone, during the last year : TF3
fh8366	EY2560: Some of YPs friends hurt or injured an animal or bird on purpose, during the last year : TF3



Acronyms	Factors (summarized)
Brk	friends involved in burglary
Drg	friends involved in drug offence
Vio	friends involved in perpetration of physical abuse

Social cohesion

Index	Acronyms	Items
fh8062	Tlk	Number of adult neighbours the participant talks to, at least once a month
fh8064	Hlp	Number of adult neighbours the participant feels they could ask for help
fh8065	FrA	Number of adult neighbours that are friendly
fh8066	FrY	Number of young people that are friendly

Direct informal social control in neighbourhood (move on)

Index	Acronyms	Items
fh8070	AHn	Adults try to move on young people if young people were hanging around the streets
fh8072	ASp	Adults try to move on young people if young people were writing/spraying paint
fh8074	ASh	Adults try to move on young people if young people were shouting/swearing at adults
fh8076	AFg	Adults try to move on young people if young people were fighting in the street

Indirect informal social control in neighbourhood (call police)

Index	Acronyms	Items
fh8071	PHn	Adults call the police if young people were hanging around the streets
fh8073	PSp	Adults call the police if young people were writing/spraying paint
fh8075	PSh	Adults call the police if young people were shouting/swearing at adults
fh8077	PFg	Adults call the police if young people were fighting in the street