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Environmental exposure during travel: A research review and suggestions forward

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ABSTRACT

Daily travel through the urban fabric exposes urban dwellers to a range of environmental conditions that may have an impact on their health and wellbeing. Knowledge about exposures during travel, their associations with travel behavior, and their social and health outcomes are still limited. In our review, we aim to explain how the current environmental exposure research addresses the interactions between human and environmental systems during travel through their spatial, temporal and contextual dimensions. Based on the 104 selected studies, we identify significant recent advances in addressing the spatiotemporal dynamics of exposure during travel. However, the conceptual and methodological framework for understanding the role of multiple environmental exposures in travel environments is still in an early phase, and the health and wellbeing impacts at individual or population level are not well known. Further research with greater geographical balance is needed to fill the gaps in the empirical evidence, and linking environmental exposures during travel with the causal health and wellbeing outcomes. These advancements can enable evidence-based urban and transport planning to take the next step in advancing urban livability.

1. Introduction

Travel environments affect people's travel behavior, shape the health and wellbeing of populations, and affect the livability of urban areas (Anciaes and Jones, 2020; Nieuwenhuijsen, 2020; Widener and Hatzopoulou, 2016). Developing fair, healthy and sustainable cities benefits from information on travel environments and their health and wellbeing impacts on populations. Street-level greenery, low congestion levels and attractive active travel infrastructure support active and low-carbon travel behavior (Le et al., 2018; Nieuwenhuijsen, 2020; Sarkar et al., 2015; Vich et al., 2019). A pleasant travel environment and active travel thus prevent traffic emissions and are associated with health and wellbeing benefits through increased physical activity (de Nazelle et al., 2011; Van Schalkwyk and Mindell, 2018; Winters et al., 2017), restorative environmental exposures (Berto, 2014; Gatrell, 2013; Wang et al., 2019), and travel satisfaction (De Vos and Witlox, 2017; Ye and Titheridge, 2017). Furthermore, access to safe, convenient and enjoyable walking, cycling and public transport networks helps reduce the determinants of socio-spatial health inequalities, being one of the cornerstones of urban livability (Anciaes and Jones, 2020; Badland and Pearce, 2019).

A car-dominant transport system exposes people to traffic pollution and other environmental disturbances, depending on the travel mode they take (Van Schalkwyk and Mindell, 2018). Motor vehicle traffic has been identified as one of the dominant contributors to urban environmental pollution (EEA, 2014; Karagulian et al., 2015), causing annoyance, increased stress, respiratory and cardiovascular diseases, and premature mortality (Khreis et al., 2016; WHO, 2000), and decreasing the prospects for walking and cycling (Widener and Hatzopoulou, 2016). It has been shown that people walking or cycling are especially vulnerable to traffic-related air pollution due to the absence of shelter from ambient pollution and more intense inhalation (Sabapathy et al., 2015; Velasco et al., 2019). Air pollution is the fifth leading risk factor for mortality worldwide and it is estimated that 91% of the global population do not breathe clean air (WHO, 2018a). On average, the residents of low- and middle-income countries are exposed to higher

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levels of air pollution than the residents of high-income countries (HEI, 2019). Similarly, low socioeconomic status communities tend to experience the highest levels of air pollution at the local level, but the evidence on health inequalities in Europe is mixed (Hajat et al., 2015).

The current knowledge on travel time exposures and their associations with health and wellbeing outcomes remain fragmented and limited. Conventional environmental exposure research focuses on singular residential exposures such as neighborhood-level air pollution, noise or greenery, as recent studies have highlighted (Helbich, 2018; Kim and Kwan, 2021; Yoo et al., 2015). This static assessment is characterized by contextual uncertainties in space and time (Kwan, 2012, 2018). People experience various simultaneous exposures in multiple locations and at multiple times in their daily life (Chaix et al., 2012). Therefore, ignoring human mobility, the dynamics of environmental conditions and cumulative effects may lead to significant biases in exposure estimates (Ragettli et al., 2015; Yoo et al., 2015; Yu et al., 2018), deficient evaluation of exposure outcomes (Dhondt et al., 2012; Dias and Tchepel, 2018; Park and Kwan, 2017; Tao et al., 2021), uninformed policies, and poor decision-making (Nieuwenhuijsen, 2016; Ramirez-Rubio et al., 2019).

During the last few decades, the dynamic aspects of human-environmental encounters have started to emerge in environmental exposure research. Similarly, transportation research is increasingly interested in travel quality (Anciaes and Jones, 2020; Khreis et al., 2017). Significant conceptual, methodological and technological advancements have enabled the acknowledgment of the role of place, time and context in the dynamic interactions between environmental and human systems (Chaix et al., 2012; Helbich, 2018; Kestens et al., 2017; Steinle et al., 2013). In particular, contemporary observational and computational measures have enhanced the prospects of capturing the complexity. The development of accurate and low-cost environmental, locational, behavioral and biophysical sensing technologies allows multiple high-resolution collections of data over time and space (Chaix, 2018; Nieuwenhuijsen et al., 2014; Reis et al., 2015; Steinle et al., 2013). The advances in modelling systems allow detailed understanding of environmental and mobility dynamics (Anda et al., 2017; Khan et al., 2018). Most importantly, new tools and methods enable the coupling of environmental and behavioral data both through spatial and temporal dimensions (Nieuwenhuijsen et al., 2015; Rabinovitch et al., 2016). These developments have resulted in dynamic exposure assessment, involving personal, activity space or population mobility exposure assessment (see, e.g., Chaix et al., 2012; Kwan, 2018; McAlexander et al., 2015; Nazarian and Lee, 2021; Perchoux et al., 2019; Song et al., 2018). Part of this research field specifically examines environmental exposures that people experience when being on the move. Physical movement through travel environments raises specific fronts for exposure research: in addition to capturing the dynamics of environments and behavior in space and time, researchers aim to understand the effects of travel mode, travel time, route choice or physical activity on exposure measures and health impacts. Furthermore, methodological questions similar to other travel-related research fields arise, such as self-selection bias in route and destination decisions (Chaix et al., 2013; Handy et al., 2006; Perchoux et al., 2019; Zhang et al., 2020) or the buffer size effect for capturing correct contextual information (Lee and Kwan, 2019; Siła-Nowicka et al., 2016). Rapid advancements suggest new potential for exposure research addressing travel environments, but also call for understanding the status quo of the research field. In this article we describe a scholarly literature review the aim of which was to answer some of the pending questions: Have recent advancements enabled us to understand environmental exposures during travel, both at the level of individuals and populations? Do we know how the exposure patterns during travel affect the health and wellbeing of traveler groups? Can we analyze the equity of opportunities to access healthy and pleasant travel environment? We frame our literature review around the argument that in order to understand environmental exposures during travel and their outcomes, we need to capture the characteristics and mutual interactions of people, travel and environment concurrently in space and time (Fig. 1).

We have dissected the current environmental exposure literature and seek to understand how this research addresses the interactions between human and environmental systems during travel through their spatial, temporal and contextual dimensions. We examined the data, methods and measures used in the travel-related exposure assessment, and which connections are made to the health and wellbeing of people. In this paper, we discuss the recent advances in the research field, existing spatiotemporal and content biases in the current body of scholarly literature, and the trade-offs between personal- and population-level exposure assessments when addressing movement. We have related the exposures encountered during travel to the discussions on sustainable and equitable transportation, and urban livability more broadly. Finally, based on our findings, we provide an agenda for further research on environmental exposures during travel.

2. Material and methods

We based our literature review on the Web of Science Core Collection (WoS), Scopus and PubMed electronic scholarly databases. We selected studies for the review with the following criteria. First, the study should be published as an original research article in an international peer-reviewed journal in English. Second, the study should include and combine data on the physical environment (e.g., air quality, noise levels or greenery) and daily mobility (e.g., commuting or other daily travel with locational information) to assess the environmental exposure during travel. Also, studies that examined environmental exposure more broadly (such as activity space or population mobility exposure), were included if details of daily travel could be extracted. Third, the exposure assessment should include empirical analysis on exposure to enable state-of-the-art mapping of this research field.

We extracted studies from the databases on 4 Feb 2020. We started the selection by using the below search phrase on title, keywords and abstract of the scholarly papers:

> "environmental exposure" OR "exposure assessment" OR "personal exposure" OR "individual exposure" OR "momentary assessment"
>
> AND
>
> "activity space" OR "spatio-temporal" OR "spatiotemporal" OR "spatiotemporally" OR "spatio-temporally" OR "context" OR "contextual" OR "geography" OR "geographic" OR "land use" OR "landuse"
>
> AND
>
> "activity space" OR "mobility" OR "transportation" OR "transport" OR "cycling" OR "commuting" OR "commute" OR "walking" OR "travel" OR "journey".

Our keyword search involved mandatory conditions for capturing studies (i) from the environmental exposure research field, (ii) that include exposure outside residential neighborhood settings, and (iii) that involve the physical travel component in particular. We did not specify environmental variables such as air pollution, noise, heat or greenery in our keyword search in order not to limit or direct the results to these environmental exposures only.

The search returned 1558 titles. We filtered our result by leaving out studies published as other than journal articles in English (N = 247), and duplicates (N = 307) (Fig. 2). This filtering left us with 1004 unique studies for abstract level scanning (see the list of studies in the **Appendix**). In this stage we excluded an additional 799 studies for the following reasons. First, we excluded articles due to the mismatch in the research field, such as studies on the mobility of substances in soils or human tissue, studies covering exposure to socioeconomic environment such as food spaces or neighborhood disadvantages, built-up land

Fig. 1. Environmental exposure during travel is an interplay between people, their travel behavior and the surrounding travel environment. Understanding and analyzing exposure during travel comes with several choices: who are the people to be analyzed, what modes of transport are analyzed, and what environmental factors are considered. Understanding exposure during travel calls for detailed data and shared research protocols on all three aspects, on a human scale.

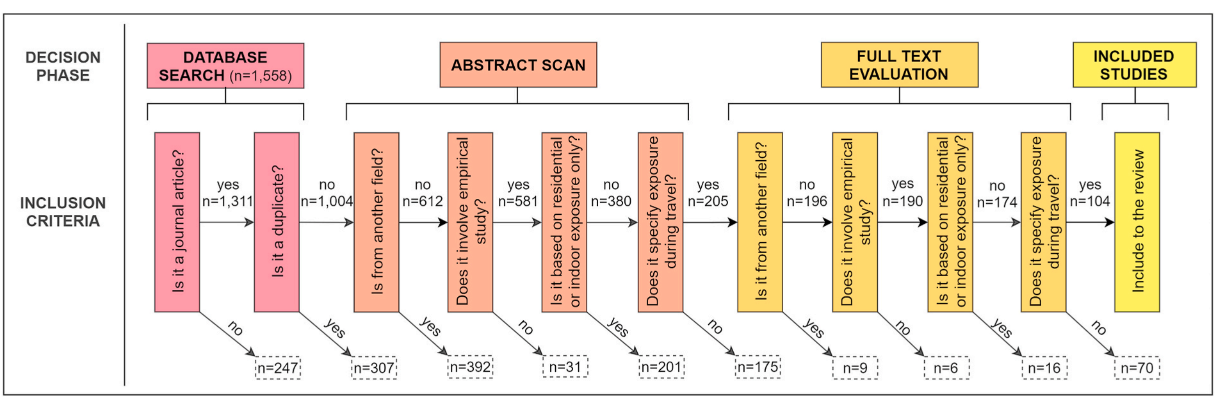

Fig. 2. The decision chain for choosing the studies for the literature review, including the number of studies included/excluded in each step.

characteristics, or disaster management. This restriction also left out studies that examined the effect of travel environments on travel behavior. Second, we excluded reviews and conceptual articles that did not contain empirical research. Third, we omitted studies that failed to convey details on exposure during physical movement. These were studies that explored environmental exposure only from the residential neighborhood perspective or solely in indoor conditions, but also studies that represented activity space or population mobility exposure perspective without capturing environmental exposure during travel episodes. Fourth, we left out studies that failed to couple travel data within an environmental context (such as mapping or modelling either environmental or mobility data only). After an abstract scan, we ran a full text evaluation on 205 studies from which we excluded an additional 101 studies based on the same criteria as above. Finally, we identified 104 relevant studies for the literature review (Appendix).

For the selected studies, we recorded 1) the scope and spatial location of the study, 2) the dominant data sources and research methods, 3) the spatiotemporal dimensions of environmental and travel data, 4) the measures and type of environmental exposure applied, 5) the presence of details enabling the comparison of exposures per travel modes, travel times or travel routes, and 6) the health and wellbeing outcomes that had been analyzed. We documented the academic journals in which the studies had been published as a proxy for the research disciplines the study belonged to.

3. Findings

3.1. Geographical, temporal and disciplinary distribution of studies

We identified 104 studies that reported findings on environmental exposure during travel. They were published between 1983 and 2020. 60% of the studies were published after 2015. These studies covered 131 study areas in 33 countries on six continents. 77% of the studies examined North America (N = 41) or Europe (N = 39), while 21% of studies focused on Asia (N = 22), leaving Oceania (N = 4), Africa (N = 2) and South America (N = 1) underrepresented (Fig. 3). In terms of

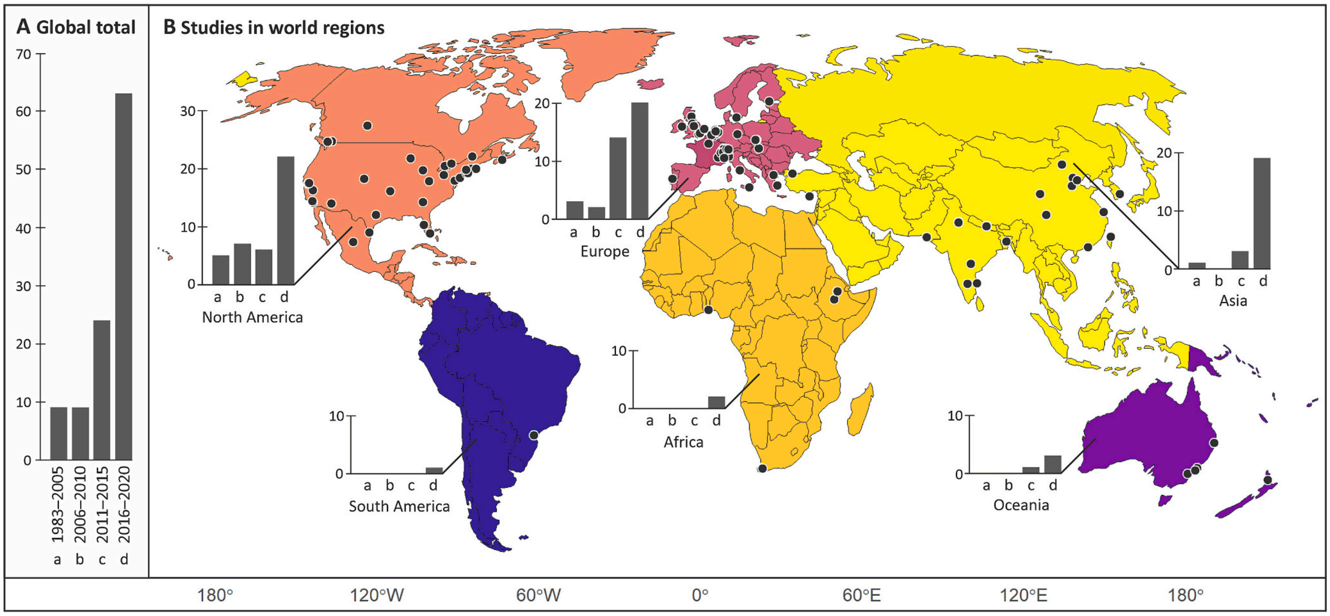

Fig. 3. The number of studies published globally in different year ranges (A), and the spatial distribution of studies in different world regions using the same year ranges for the bars (B). The locations of individual study sites are indicated as points on the map (B).

individual cities, the highest number of studies were conducted in Vancouver, Montreal (both n = 7), Los Angeles (N = 5), Barcelona, Basel (both N = 4), and Dublin, Ghent, Hong Kong and Toronto (in all of these, N = 3).

Most of the studies were published in journals in the fields of environmental science and environmental health, with the three most often-featured journals being *Atmospheric Environment*, *Science of the Total Environment* and *International Journal of Environmental Research and Public Health*. There were fewer studies published in the journals related to transport, geography or GIScience. In this field, at least two studies were published in these journals: *Computers, Environment and Urban Systems*, *Transportation Research Part D: Transport and Environment,* and *Sustainable Cities and Society*.

3.2. Environmental contexts

Most of the studies (93%) concentrated on exposure to air pollution (Fig. 4A). Other environmental variables that were addressed included noise, temperature, greenery, radiofrequency electromagnetic field and chemicals present in the surrounding dust. Few of the studies (5%) explored exposure to at least two different environmental variables at the same time, such as combining air pollution and noise exposures.

Environmental data about the travel environments were most often captured with the help of portable sensors (in 65% of the studies) or fixed-site sensors (40%), and 46% of the studies applied land use, meteorological or other external data in environmental modelling (Fig. 4B). Data collection via observations (69%), modelling (50%) or mapping (6%) resulted in storing and presenting environmental data

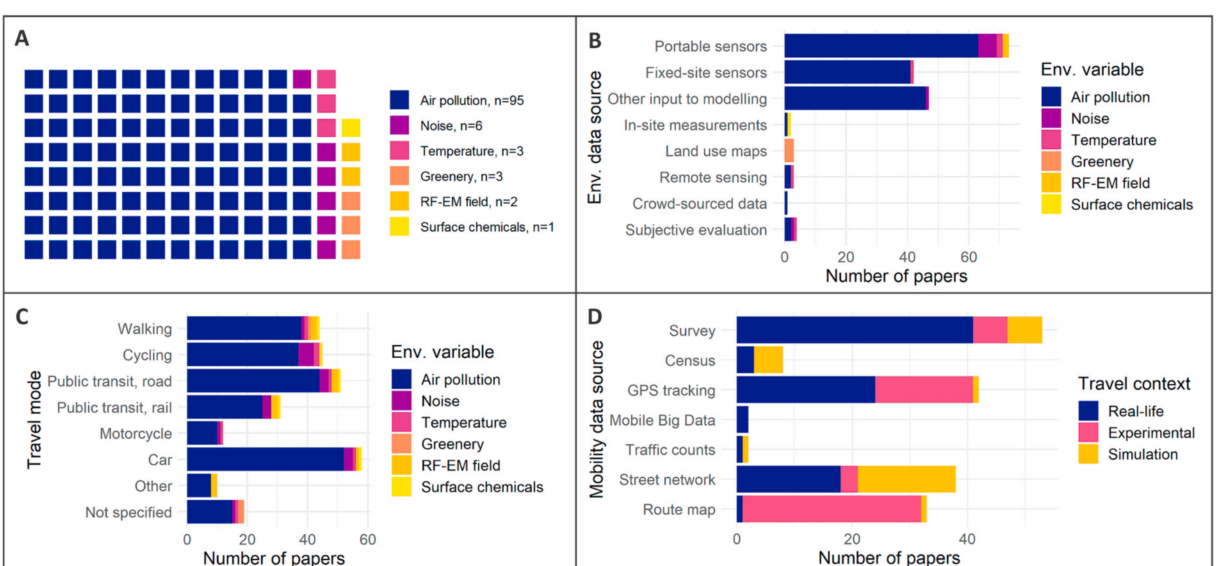

Fig. 4. Environmental variables and travel attributes addressed in the reviewed travel-related exposure studies: (A) the number of studies per environmental variable, 1 block = 1 study; (B) environmental data collection methods per environmental variable; (C) examined environmental exposure per travel mode; (D) travel data collection methods per mobility type. The studies may be counted more than once if they cover multiple variables, methods, travel modes, or mobility types.

layers either as routes (69%), surfaces (40%) or single points (5%) (**Appendix**). While most studies involved environmental data from outdoor travel environments (93%), then 57% of the studies explored exposure in the context of in-vehicle microenvironments.

Most of the studies (84%) captured the temporal changes in environmental conditions, and 16% of the studies used static environmental data. Portable sensors that are able to represent the temporal dynamics of environmental conditions were used to record the state of environmental conditions even up to every second (17% of all studies). Environmental data captured from fixed-site monitoring stations or modelling systems were typically collected with an hourly interval (31%). In most cases, the data collected on short intervals were aggregated to longer time spans to compute average exposure estimates (trip, hourly, peak and off-peak, daily, seasonal, annual) or cumulative exposure estimates (daily, annual).

3.3. People in travel and travel types

We found that 65% of the studies analyzed travel-related exposure among certain population or traveler groups such as school children, cyclists or commuters. The rest of the studies explored exposure among residents more broadly. The sample sizes varied from one person (3% of the studies) to a wide coverage of residents (8% of the studies involved samples with 10,000 or more people). 37% of the studies did not involve a sample and 9% of the studies estimated exposure during travel based on modelled populations.

The studies concentrated on real-life travel behavior (54%) but also used experimental settings (36%) or mobility simulations (17%). The real-life travel data represented people's travel behavior mainly from short data collection campaigns lasting from one day up to a week (44% of the studies and 82% of those studies using real-life travel data). Only six real-life studies explored exposure during travel over longer time spans. On the other hand, experimental exposure studies tended to collect travel data over longer durations: 25% of all studies and 70% of the studies using experimental designs collected data from assigned or freely-chosen routes over time spans longer than one week.

Most of the studies identified exposure while people were using a particular travel mode (83%; Fig. 4C). 66% of the studies covered motorized transport (public transit, car, motorcycle, other) and 56% active travel modes (walking or cycling). The studies about active travel addressed environmental variables other than the dominant air pollution more frequently than the studies covering motorized travel (19% and 11% of those studies, respectively). 42% of the studies compared resulting exposure measures between at least two travel modes (details in **Appendix**). Route or areal level differences in travel-time exposure measures were considered in 56% of the studies. 57% of the studies compared exposure measures between the times of travel, such as peak and off-peak times or seasons.

The main sources for travel data collection were surveys (applied in 45% of studies), tracking with GPS-equipped devices (39%), street network layers (29%) and route maps (31%; Fig. 4D). Survey techniques such as activity diaries, interviews or questionnaires were mostly applied to capture real-life travel behavior, and these techniques were used in 73% of all real-life mobility studies. In 15% of the studies, survey techniques also complemented real-life or experimental travel data that were collected with GPS-equipped devices. Street network data served routing purposes mostly in studies based on real-life travel information or mobility simulations to locate trips between defined origins and destinations. Route mapping was mostly applied in experimental studies that followed assigned routes for environmental data collection.

3.4. Dynamic exposure analysis

Most of the studies acknowledged the temporal dimension of environmental exposure (96%), leaving only 4% of studies with fully static exposure estimates. Fully dynamic, time-weighted exposure estimates were presented in 72% of the studies (Fig. 5). These studies considered the temporal dynamism of both environmental conditions and the timing and duration of travel. Fully dynamic assessments were supported by sensor techniques that enable collection of both data sets simultaneously, or by a spatiotemporally precise modelling approach that allowed the co-location of people with their environmental conditions both in space and time. Time-weighted exposure estimates were also presented in the studies that applied static environmental data but recorded the duration of travel in certain environmental conditions (13%). Other studies in which the dynamic approach was used (12%) monitored exposure along certain routes or in certain transport microenvironments to find average exposure intensities without individual trip attributes.

3.5. Impacts of exposure

The studies applied several exposure measures (Fig. 6) mainly in the form of passive, 'external' measures (97%). These characterize either the prevalence of encountering certain environmental conditions (5%), such as greenery during travel, average exposure intensities in certain travel environments (63%), time-weighted personal exposure during travel (59%) or population level exposure (9%).

Next to the 'external' exposure measures, several studies (30%) analyzed exposure 'internally', from the perspective of the human body. The examples include inhaled dose of air pollution (19%) that depends not only on ambient or microenvironmental air quality, but also on the intensity of physical activity during travel. A few studies (4%) examined the presence of biomarkers or heart rate variability. In addition to objective measurements, one paper investigated how people perceive environmental stressors during travel and how that correlates with objective measurements.

Some of the studies using 'internal' exposure measures elaborated the active interaction between the environment and the human body further on to detect direct health response to exposure situations. These health impact assessment-related studies mainly reported negative health effects (6%) of air pollution exposure such as respiratory symptoms or decreased cognitive parameters. Only one study brought to focus positive health effects by addressing how greenery exposure during daily travel in early life is associated with better cognitive aging in later life.

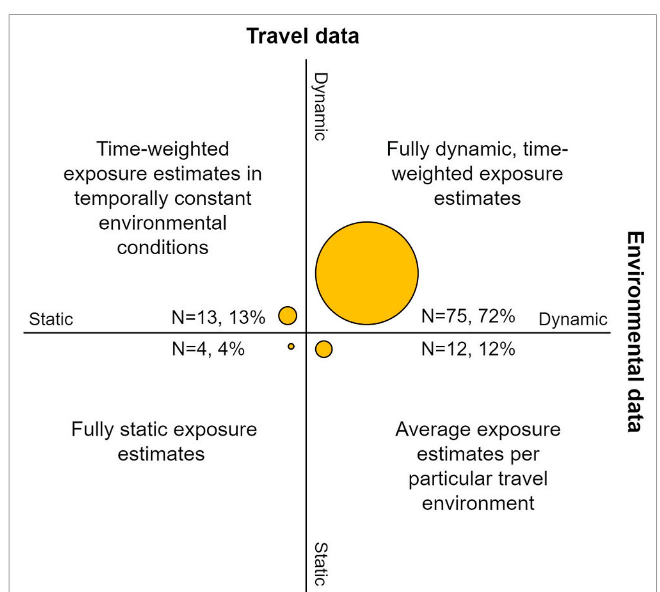

Fig. 5. The distribution of studies from fully dynamic to fully static exposure estimates based on the approach to environmental and travel duration data.

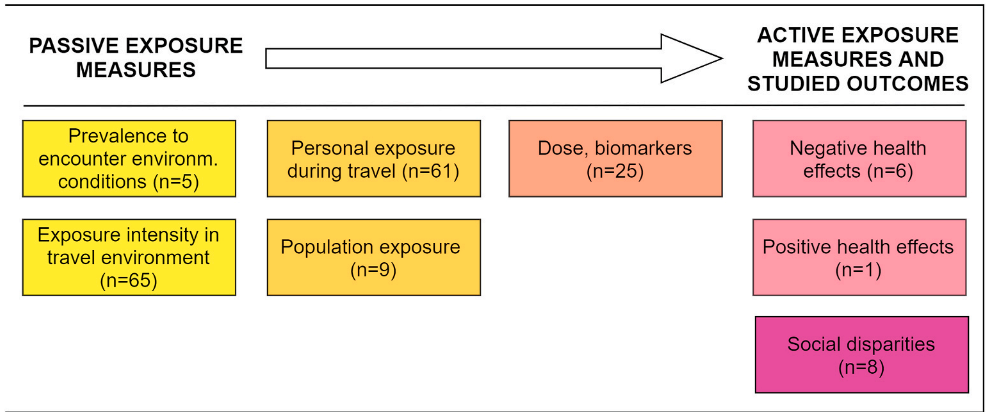

Fig. 6. The depth of exploring environmental exposure measures and outcomes. Number of reviewed studies given in parenthesis.

A further analytical step was presented by studies that aimed at understanding the social consequences of environmental exposures (8%) such as socio-environmental and health disparities stemming from disproportionate exposure to beneficial or harmful environments. These articles studied the association between exposure estimates and the socio-demographic characteristics of the individuals or population groups exposed.

4. Future research directions

The results of this literature review suggest that analysis of environmental exposure during travel is an emerging research field with significant recent advances in addressing spatiotemporal dynamics of environmental conditions and human mobility. Our review shows an increasing acknowledgment of the quality of travel environments, and exposure during travel as a factor affecting the health and wellbeing of people. We note that the research field has significant potential to serve the goals of urban sustainability and wellbeing. Early studies on microenvironmental and personal exposures during travel date back as far as to the 1980s and 1990s (see Brauer and Brook, 1997; Holland, 1983; Jo and Park, 1999). However, most studies on the topic have been published during the last five years, demonstrating a clear and increased interest on the topic. Active attention on dynamic exposure assessment in travel context has been evident also after the date we conducted our keyword search, bringing new evidence, among others, on multiple exposures (e.g., Marquart et al., 2021; Tao et al., 2021). However, the literature review shows that the emerging research field is still immature in many aspects and there is a need for further research. Below, we summarize and discuss our main findings and use them to create a research agenda for the future.

Environmental exposure during travel requires distinct attention to break disciplinary silos. To better resonate with transportation research and the discussions on sustainable travel environments, travel time exposure assessment requires distinct attention within the broader field of dynamic exposure assessment. Environmental exposure during travel is reported to be disproportional to the time people spend in travel (de Nazelle et al., 2013; Milà et al., 2020; Shekarrizfard et al., 2016). Overlooking travel episodes may lead to under- or overestimation of exposure when compared with environmental exposures in residential neighborhood (see also Kim and Kwan, 2021; Setton et al., 2011; Tang et al., 2018) or other activity locations (de Nazelle et al., 2013). The biases occur because the ambient environmental conditions differ in space and time, including along or between the routes (Li et al., 2017; Minet et al., 2018; Park et al., 2017; Van den Hove et al., 2020), and each travel mode exposes people differently to the environment (Grana et al., 2017; Jain, 2017; Kam et al., 2011; Onat et al., 2019; Zuurbier et al., 2010). As such, the key aspect is coupling travel modes, routes and times with the respective details of the environmental conditions in travel (micro)environments. The currently used terms within the broader dynamic exposure research, such as personal, activity-space based, mobility-based, microenvironmental, momentary or population mobility assessment, do not reveal whether the study design aims to capture exposure during the events of movement and distinguish travel episodes in the results. We therefore propose the extension 'during travel' to distinguish the focus of exposure assessment on physical movement from other types of mobility.

Comparable research would benefit from shared protocols. The future research agenda should aim to provide thorough meta-analyses on the published evidence of the multiple environmental exposures people encounter during travel, and related health and wellbeing outcomes. However, this comes possible only with more studies using more standardized and hence comparable research practices. There is a myriad of methodological complexities to be tackled, such as the comparability of exposure and health response measures (see, e.g., de Nazelle et al., 2013; El Aarbaoui and Chaix, 2020; Gouge et al., 2010), the variation, and transformation of environmental variables, their combination with traveler behavior and related health effects (see Alvarez-Pedrerol et al., 2017; Apparicio et al., 2018; Keskin and Dilmac, 2017; Ragettli et al., 2015), or the effects of vehicles, traffic density, travel infrastructure or land use characteristics (see Gouge et al., 2010; Hankey et al., 2017; Spinazzè et al., 2015; Weichenthal et al., 2015). Also, the effects of meteorological conditions and seasonal changes need to be considered (see Jain, 2017; Onat et al., 2019; Thai et al., 2008). Population level analysis requires representative samples (see Saraswat et al., 2016; Tang et al., 2018; Yasumoto et al., 2019). In order to make exposure studies more comparable, we call for shared protocols for carrying out the research.

Broader global research coverage would help mitigate geographic bias. Our review highlights a geographic bias in international scholarly literature of exposure during travel towards western cities where the history of research in this field is longer. At the same time, we see a rapid increase in the number of studies conducted in China and India (e.g., Li et al., 2019; Saraswat et al., 2016; Tang et al., 2018; Zou et al., 2020). This is an important trend as these countries face the highest numbers of premature death due to ambient air pollution (WHO, 2020). However, this growing scholarly attention on the international research arena has not yet filled the gap in research from most cities with high environmental health risks, particularly in South and Southeast Asia, the Middle East and Sub-Saharan Africa (see HEI, 2019; WHO, 2018b). Understanding and recognizing travel time exposures and how different population groups are exposed to environmental conditions during travel in specific local contexts would support transport and urban planning in these and other regions to better mitigate the risk of environmental health disparities. This is especially relevant in cities that are also facing rapid population growth with related longitudinal changes in land use and infrastructure. Creating and ensuring access to healthy travel infrastructure in new development areas would help prevent the problems from the start. Geographically even research with open data sets and comparable methodologies would help validate research results in different spatial contexts and reduce contextual uncertainties (see also Kedron et al., 2021).

While air quality leads the way, other exposures deserve scholarly attention. With the high global rates of premature deaths (WHO, 2018a), air quality continues to be an important topic in exposure studies, as shown by our review. With the methodological advancements, air pollution research is of benefit to the whole field of exposure studies. However, scholarly literature shows that also other environmental stressors such as noise or heat may cause significant health problems (EEA, 2020; Kovats and Hajat, 2008). For example, assessing the exposure to traffic noise (e.g., Dzhambov and Lercher, 2019; Riedel et al., 2014; Roswall et al., 2015) or thermal risks (e.g., Kjellstrom et al., 2016; Parsons, 2014) is well-established in the built environment context. It has still remained scarce in dynamic contexts (see, e.g., Hu et al., 2019; Nazarian and Lee, 2021; Tao et al., 2020), which is confirmed by our results: we found only a limited number of studies of travel time exposures that address environmental stressors other than air pollution, most frequently noise (Apparicio et al., 2018; Dekoninck et al., 2013; El Aarbaoui and Chaix, 2020; Liu et al., 2019; Morley and Gulliver, 2016; Ueberham et al., 2019).

In contrast to environmental stressors, exposure to green spaces is often shown to be associated with several positive effects on health and wellbeing (EEA, 2020; Gatrell, 2013; Hartig et al., 2014; WHO, 2016). Residential neighborhood exposure assessment has a long research history in evaluating the presence and accessibility of urban green spaces (Cohen-Cline et al., 2015; de Keijzer et al., 2020; Gascon et al., 2015), with recent evidence on the effects of green travel environments in the vicinity of home (Laatikainen et al., 2018; Lu, 2018; Tsai et al., 2019). Similarly, studies in the fields of urban travel behavior (e.g., Sarkar et al., 2015; Vich et al., 2019; Yang et al., 2020; Zhang et al., 2020) or environmental psychology (e.g., Bratman et al., 2015; Navarrete-Hernandez and Laffan, 2019; Ojala et al., 2019) have addressed green travel environments as part of healthy, just and sustainable urban space. However, our keyword search returned little evidence of research on greenery exposure assessment during travel, outside the spatial scope of residential neighborhood. The existing examples addressed the effect of greenery on providing mental health benefits (Cherrie et al., 2019) or equitable urban landscape (Paddle and Gilliland, 2018).

Hence, our results suggest that environmental variables other than air quality have received less systematic attention in travel related environmental exposure research than air pollutants. While we acknowledge the limits of our keyword search in finding all relevant papers that address exposure during travel (e.g., Buonanno et al., 2014; Hertel et al., 2008; McAlexander et al., 2015; Zhang et al., 2018), particularly those conducted outside the environmental exposure research domain, we argue that the current understanding of the composition, pattern and health response of travel time exposures at large, beyond air pollution, remains limited and unsystematic. There is huge potential to increase the visibility and advance the knowledge on a wider set of environmental exposures encountered by people in travel environments by combining the traditions of urban and land use planning and environmental studies with the recent methodological advancements of dynamic exposure research.

More research is needed on the patterns and impacts of multiple and cumulative exposures. People experience many simultaneous exposures during their daily trips (Helbich, 2018) that may have cumulative health effects (EEA, 2020; Klompmaker, 2020). However, the studies we reviewed provide little evidence of the multiple concurrent exposures people encounter during travel. The few examples illustrate the dependencies and multidimensionality in the interactions between different environmental variables, mostly air pollution and noise, and the role of travel modes in determining the mutual relationship (see Apparicio et al., 2018; Dekoninck et al., 2013; Donaire-Gonzalez et al., 2019; Liu et al., 2019). The variation in correlation between different environmental variables may stem from methodological, contextual, behavioral and meteorological conditions (Khan et al., 2018) that highlight the complexity in reaching standardized and comparable approaches in exposure assessment. Furthermore, as Ueberham et al. (2019) showed, there is a variation in how people perceive different environmental variables during travel compared to objective, measured exposure, a suggestion that is reiterated also in more recent research (Tao et al., 2020). This ambiguity of multiple exposures makes their interpretation more complex and triggers a need for further research, including enhancing the understanding how multiple exposures evolve and accumulate over time, and how measured and perceived exposures affect travel behavior (see also Haddad et al., 2019; Helbich, 2018).

Crossing disciplinary boundaries could lead to a better understanding of the associations between exposure and health. Most studies limit the analysis to simple exposure estimates without exploring their effects on health and wellbeing. Only a small number of studies in the review link exposure estimates to the assessment of health response from the perspective of adverse health effects (e.g., Alvarez-Pedrerol et al., 2017; Park et al., 2017; Rabinovitch et al., 2016) or positive health outcomes (Cherrie et al., 2019). Slightly more evidence has been published on how the mode of transport affects the interaction between the human body and its travel environment through pollution inhalation (e.g., Donaire-Gonzalez et al., 2019; Hofman et al., 2018; Marshall et al., 2006; Zuurbier et al., 2010). Despite these advancements, the understanding of how health and wellbeing effects are driven from either acute or longitudinal travel time exposure patterns, remains incomplete. Overcoming methodological challenges such as the spatiotemporal coupling of environmental, behavioral, health and sociodemographic data on various scales (see, e.g., Chaix, 2018; Gurram et al., 2019; Hankey et al., 2017; Tang et al., 2018; Wang et al., 2018a) as well as crossing disciplinary boundaries between environmental monitoring, exposure science and epidemiology (Lioy, 2010) could help fill the gap.

Integrating portable sensors to a city-wide infrastructure could provide human-scale environmental data over longer time spans. The review revealed a sharp increase in the use of portable sensors and other location-aware technologies in exposure studies. Novel technologies facilitate personal exposure assessment and coupling environmental and behavioral data, and help avoid potential under- or overestimations of static exposure estimates (de Nazelle et al., 2013; Shekarrizfard et al., 2016; Simon et al., 2017; Tang et al., 2018). Furthermore, they are able to identify short term peak values in personal exposure profiles (Dons et al., 2014), reveal their diurnal, weekly and seasonal dynamics (Spinazzè et al., 2015), and detect the variation between different travel modes (Kumar et al., 2018; Velasco et al., 2019). Portable low-cost sensors used by citizen scientists show immense potential for adding spatial and temporal detail in environmental data, ranging from air quality to temperature and noise, and empower citizens to understand the role of exposures in their daily life (Huck et al., 2017). They also provide monitoring options in areas poorly covered by a stationary monitoring network (Reis et al., 2015) and may hence balance the uneven geographical distribution of exposure studies. Despite the many benefits, portable sensors alone fall short when aiming at city-wide exposure monitoring with high spatiotemporal resolution if this requires systematic human involvement. Incorporating sensors to a city-wide infrastructure of shared bikes or similar on a permanent basis and linking them to the operational air quality monitoring network could help tackle the challenge, as tested with prototype solutions in several parts of the world (Aguiari et al., 2018; Deshmukh et al., 2020; Liu et al., 2015; Velasco et al., 2016). Beyond air or noise pollution, different sensing techniques such as street view images might be more suitable for capturing the quality of the travel environment, such as the amount of street greenery, at the human eyesight level (see Li et al., 2015; Xia et al., 2021; Ye et al., 2019).

Location-aware technologies provide rich travel data, but complementary data sources are needed for scaling up travel data

collection. Most of the studies on exposure during travel operate on an individual route or trajectory level. Coupled with location-aware technologies, this is an important advancement as the studies expand the examination of exposure from residential setting to travel environments and other life domains (Kwan, 2012, 2018; Mennis and Yoo, 2018). Spatiotemporally rich data collected with the help of GPS-equipped devices or smartphones enable researchers to identify individual movements and travel modes (e.g. de Kluizenaar et al., 2017; Dewulf et al., 2016). Data collection campaigns with small samples make it possible to enrich sensor data with survey data for capturing travel-related semantics and socio-demographic background information (e.g., Bekö et al., 2015; Lei et al., 2016; Milà et al., 2020). A few studies have indicated how detailed data of the mobility of individuals collected by large platform companies, such as Google, may facilitate exposure assessment over extended time periods, or even over larger population groups (Su et al., 2015; Yu et al., 2019). Despite these perspectives, personal exposure assessments are most often based on non-representative samples and limited time spans of empirical studies, making it difficult to understand exposure during travel at the level of populations and through longer time spans. To cope with this demand of detail and extent, the use of mobile Big Data sources could be explored more in exposure studies.

Mobile Big Data may allow examining exposure at population scale. Activity-based mobility simulations and route modelling based on census or survey data (such as used by Gurram et al., 2019; Park and Kwan, 2020; Tang et al., 2018; Yasumoto et al., 2019) allow scaling up exposure research to populations, but lack real-life detail needed for contextual travel environment analysis over longer time spans. The avalanche in mobile Big Data, such as mobile phone data or data collected by various apps from social media to sports trackers, enable trip detail to be obtained over large population groups (Anda et al., 2017; Chen et al., 2016; Heikinheimo et al., 2020; Lee and Sener, 2020; Toivonen et al., 2019; Toole et al., 2015). Mobile phone data, in particular, cover large proportions of population and provide a decent spatial detail for analyzing travel time exposure patterns at least in urban areas where the antenna network is dense enough (de Montjoye et al., 2018; Gundlegård and Karlsson, 2020; Wang et al., 2018b; Zhao et al., 2021). Despite the high potential, the use of mobile Big Data does not come without challenges. Almost without exception, mobile Big Data are collected by private companies who have a full control over the access rights, and the processing methodology is seldom revealed in detail (Ahas et al., 2015; de Montjoye et al., 2018; Gundlegård and Karlsson, 2020; Poom et al., 2020; Toivonen et al., 2019). Despite the challenges, broad-scale passively collected data on population mobility are emerging in exposure research (e.g., Gariazzo et al., 2016; Li et al., 2019; Picornell et al., 2019; Song et al., 2018). Mobile big data has the potential to contribute to the longitudinal analyses of environmental exposure at the scale of urban populations, allowing also the examination of equity. Therefore, exposure researchers could raise their voice to advance the availability of these data for research use and call for more transparent processing chains (Poom et al., 2020).

Scholarly emphasis on good travel environments can advance the designing of just and sustainable cities. A few studies have incorporated socio-environmental disparity and land use analytics to understand the differences in exposure between population groups (e.g., Gurram et al., 2019; Park and Kwan, 2020; Yasumoto et al., 2019) or the equity in accessing health-promoting travel environments (Hankey et al., 2017; Paddle and Gilliland, 2018). Other authors have applied routing to identify low-exposure travel environments (e.g., Alam et al., 2018; Mölter and Lindley, 2015) or suggest urban planning measures to reduce pollution at active travel routes (e.g., Apparicio et al., 2018; Hofman et al., 2018; Kumar et al., 2018). By encouraging the discussions on the quality and equity of travel environments, these studies support the concept of just cities and equitable distribution of access to healthy travel infrastructure that in turn encourages healthy and active travel behavior. Low-pollution, green, inclusive and attractive travel environments are also linked to the sustainability and livability goals of cities, as they have been shown to influence the propensity for physical activity, the prevention of congestion and carbon emissions, and the reduction of the social gradients in environmental exposures and health inequalities (Anciaes and Jones, 2020; Badland and Pearce, 2019; Nieuwenhuijsen, 2016, 2020; Ramirez-Rubio et al., 2019). Further research is still needed to disentangle the causal pathways between travel environment, travel behavior, environmental exposure during travel, health effects, socio-spatial inequalities, and sustainability.

The pandemic highlights the value of open research practices. Since conducting our keyword search, the world has witnessed major interruptions in human mobility and travel behavior due to the global COVID-19 pandemic (Sheller, 2020; Willberg et al., 2021). Mobility restrictions have changed the purposes, times and modes of travel (Bucsky, 2020; Eisenmann et al., 2021; Venter et al., 2020). The lockdown-induced drop in the overall traffic intensity has at least temporarily improved environmental conditions in urban areas (Martorell-Marugán et al., 2021; Nie et al., 2021; Tian et al., 2021). Presumably, these changes have affected travel-time exposure patterns on both individual and population level. Understanding the changes in realized exposures and related health and wellbeing effects would help us learn how to plan and govern our cities to be more resilient, equitable and livable in different times. The research community can study the changes best if we manage well our data, including opening up data sets from the times before and during the pandemic, and follow open, transparent and replicable research practices (Kedron et al., 2021).

5. Conclusions

Environmental exposure research has recently added the spatio-temporal dimension of environmental dynamics and human mobility to its research agenda. However, the conceptual and methodological framework for understanding the role of multiple environmental exposures during travel is still emerging, and the health and wellbeing effects to be realized are not well known. Integrating the expertise of transport and geospatial researchers, environmental scientists, sustainability and welfare scholars, and the traditions of health and exposure research could advance the understanding of the importance of travel time exposure in cities. Further research with greater geographical balance is needed to fill the gaps in the empirical evidence and causal pathways of the health and wellbeing outcomes of the environmental exposures encountered during travel. These advancements can enable evidence-based urban and transport planning, and truly advance urban livability.

Appendix

The list of extracted papers and the details of the papers reviewed.

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Author Contribution

Age Poom: Conceptualisation; Methodology; Data curation; Formal analysis; Investigation; Visualization; Writing – original draft, review and editing; Project administration. Elias Willberg: Conceptualisation; Visualization; Writing – original draft, review and editing. Tuuli Toivonen: Conceptualisation; Visualization; Writing – original draft, review and editing; Supervision; Project administration; Funding acquisition.

Declaration of competing interest

None.

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Appendix A. Supplementary data

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