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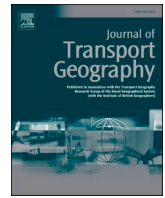
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Bridging or separating? Co-accessibility as a measure of potential place-based encounters

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ABSTRACT

Accessibility is a widely used concept across various disciplines to evaluate the degree to which individuals can reach desired destinations. Conventionally, accessibility is determined by the attractiveness of a destination and the associated travel cost to reach it. However, existing place-based accessibility measures do not differentiate between destinations accessible to individuals from a single demographic group and those accessible to individuals from diverse demographic groups. We propose a measure to assess the potential of distinct destinations to bring different individuals and demographic groups together, defining this property as co-accessibility. We demonstrate how measuring co-accessibility can enhance existing accessibility measures, describe its components, and provide a mathematical formulation for quantifying it. To illustrate the practical application of our measure, we conduct a case study in Amsterdam, the Netherlands, comparing the accessibility and co-accessibility of various destinations. This sample case study highlights the complexities and challenges inherent in measuring co-accessibility. Building on existing literature and our analysis results, we discuss the potential implications of co-accessibility, identify key challenges in its assessment, and recommend directions for future research.

1. Introduction

Accessibility serves as a fundamental concept across diverse disciplines, including land-use planning, transportation planning, and urban design, wherein it plays a pivotal role in assessing the ease with which individuals can reach essential activities and services, together referred to as opportunities (Hansen, 1959; Pirie, 1979; Geurs and Van Wee, 2004; Batty, 2009; Levine, 2020; Handy, 2020). There are various approaches to measuring accessibility, but one prevailing and widely accepted principle is that accessibility is determined by the attractiveness of a desired destination and the associated cost required to reach it (Handy and Niemeier, 1997; Geurs and Van Wee, 2004; Levinson and Wu, 2020). The attractiveness of a destination encapsulates a variety of factors, such as the number and type of activities, amenities provided, or employment opportunities available at that location. In turn, travel cost could refer to time, monetary expenditures, or other costs required for an individual to reach a desired location.

The concept of accessibility, including its associated measures and mathematical formulations, has been further specialized into *active* and *passive* accessibility. Active accessibility reflects the ease with which an

individual can reach a destination or engage in activities at a specific location (e.g., work, education, leisure). It is the most prevalent conceptualization of spatial accessibility and aligns with the fundamental definition of Hansen (1959). In contrast, passive accessibility indicates the ease with which an opportunity can be reached by the population (Pirie, 1979; Papa and Coppola, 2012; Cascetta et al., 2013). Despite their considerable potential and expanding applications, passive accessibility measures have received limited attention compared to measures of active accessibility (Cascetta et al., 2013; Lopes et al., 2019; Lee and Salih, 2024). In both cases, the optimization of accessibility entails maximizing the attractiveness of destinations while minimizing the costs for individuals to reach them. Nevertheless, this optimization goal exhibits certain limitations. For active accessibility, it cannot differentiate between various destinations being accessible to different individuals and the same destination being mutually accessible to multiple individuals. In contrast, passive accessibility measures can overcome this shortcoming by considering the number of people who have access to each destination. However, most passive accessibility measures have another limitation: they do not differentiate between destinations accessible to individuals from a single demographic group and those accessible to individuals from

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diverse demographic groups. Given that access to shared spaces is critical for physical encounters and interactions among different individuals and groups (Levine et al., 2019; Lanza et al., 2023), these limitations hinder our ability to understand the potential of destinations to facilitate such encounters.

Considering the shortcomings of both active and passive accessibility measures, this article introduces *co-accessibility* as a measure for evaluating the extent to which a destination is mutually accessible to individuals from various demographic groups (e.g., age, ethnicity, income). Co-accessibility accounts for the differences in factors influencing accessibility for each demographic group. These factors may include available travel modes, types of activities, and the needs and preferences specific to different demographic groups or individuals. Our proposed measure can be used to examine segregation phenomena by extending research beyond the usual focus on residential, workplace, and educational environments (Miliás and Psyllidis, 2022). Additionally, co-accessibility metrics could guide the design of destinations to better meet the preferences and needs of the diverse individuals and demographic groups who can access them.

In the following sections, we examine existing accessibility measures, highlight some of their inherent limitations, and illustrate how co-accessibility might transcend these constraints. We then define the fundamental constituents of co-accessibility and provide a mathematical formulation for quantifying it. In highlighting the intricacies and challenges involved in the measurement of co-accessibility, we use a sample case study to evaluate and compare pedestrian accessibility and co-accessibility across various destinations in Amsterdam, the Netherlands. Drawing upon the existing literature and the outcomes of our analysis, we investigate the potential implications of co-accessibility, underscore the main challenges in its measurement, and suggest avenues for future research.

2. From accessibility to co-accessibility

The conceptualization of accessibility and approaches to measuring it vary between studies and across disciplines. A shared principle driving most approaches is that accessibility is determined by the distribution of potential destinations across space, the characteristics of these destinations, and the ease of reaching them (Handy and Niemeier, 1997). The most common mathematical formulation of accessibility in the literature builds upon the seminal work of Hansen (1959), and is defined by two main components: the attractiveness of destinations and the associated costs required to reach them. Following the notation of Levinson and Wu (2020), its formulation is given by:

$$A_i^j = \sum_{j=1}^J O_j f(C_{ij}) \quad (1)$$

where A_i^j denotes the accessibility of origin location or zone i to destination or zone j ; O_j is the destination attractiveness, often reflecting the number of opportunities available at destination j ; and $f(C_{ij})$ is the cost or impedance to reach destination j from origin i . Eq. 1, formally defines active accessibility but can be used for both active and passive accessibility depending on what zone i and j represent (i.e., location of individuals or opportunities) (Levinson and Wu, 2020).

Over the years, numerous metrics have emerged in the literature that expand Hansen's formulation, aiming to capture the multi-dimensional nature of accessibility (Wu and Levinson, 2020). Some of these extended metrics enrich the cost component (C_{ij}), considering different travel modes and traffic conditions (Moya-Gómez and García-Palomares, 2015), time schedules of individuals, (Hägerstrand, 1970; Miller, 1991; Neutens et al., 2008; Tang et al., 2016), individual perceptions of travel costs (Carrion and Levinson, 2019), or how different population subgroups such as minorities or persons with disabilities experience access (Martens, 2016). Additionally, the destination

attractiveness (O_j), initially used to reflect the number of accessible destinations or jobs in area j (Hansen, 1959; Geurs and Van Wee, 2004), has evolved to encompass a wider array of factors pertaining to why individuals are attracted to particular destinations. This includes considerations such as the type of activities at a destination, the size and quality of facilities, or individuals' lifestyle-based preferences (Kitamura et al., 1997).

To encompass and distinguish the various perspectives within accessibility-related literature, existing measures have been categorized in several ways. Measures of either active or passive accessibility can be further distinguished into place-based and person-based measures (Hägerstrand, 1970; Miller, 2005; Kwan, 2009). Place-based measures assess the spatial separation of different locations. Such locations often represent individuals' anchor locations (e.g., home or work) and key destinations where activities occur. Person-based measures reflect the extent to which individuals or specific groups can access different destinations while accounting for each individual's spatial and temporal constraints.

Levinson and Wu (2020), building on Hansen's formulation (Eq. 1), proposed a generalized measure of accessibility to encapsulate all the different considerations of spatial accessibility (Eq. 2). This formulation, while similar to Hansen's Eq. 1, allows a shift from partial to general access (Levinson and Wu, 2020) by representing A_i , O_j , and C_{ij} as matrices. These matrices enable accounting for different types of destinations, times of day, time availability, travel modes, and all costs related to accessing a destination (e.g., money, noise, or congestion). In addition, function g is used to reflect the unequal value of destinations.

$$A_i = \sum_{j=1}^J g(O_j) f(C_{ij}) \quad (\text{active}) \quad (2)$$

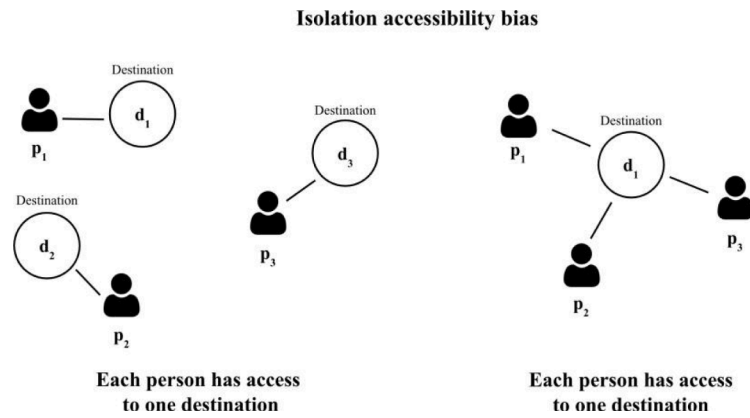
$$A_i^{\cup} = \sum_{j=1}^J g(O_j) f(C_{ji}) \quad (\text{passive})$$

Both active and passive accessibility measures have specific limitations. Active accessibility measures do not distinguish between different destinations being accessible to different individuals and the same destination being accessible to multiple individuals, a limitation we term *isolation accessibility bias*. Passive accessibility measures can address this bias. However, passive measures often erroneously equate a destination accessible to individuals from a homogeneous group to a destination accessible to individuals from diverse demographic groups, a limitation we term *homogeneity accessibility bias*.

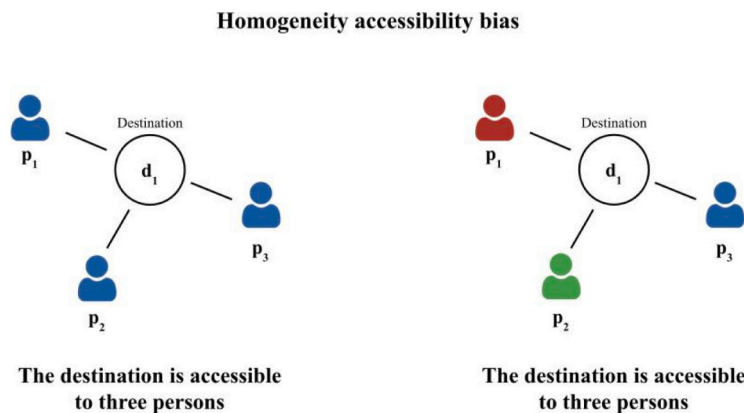
To illustrate these biases, we present two examples inspired by the schematic activity space representation proposed from Flamm and Kaufmann (2007) and Perchoux et al. (2013) and depicted in Fig. 1a and b. This representation serves as a means to depict the destinations an individual can access using links to denote people's mobility paths and nodes to represent the destinations they have access to.

Fig. 1a illustrates the *isolation accessibility bias* by contrasting two cases. On the left, there are three destinations (d_1, d_2, d_3) and each destination is accessible to one individual. On the right, the same single destination (d_1) is accessible to all three individuals. While these two cases are different in terms of the number of individuals who have access to each destination they are not differentiated when solely examining the number of destinations each individual has access to (one destination).

Fig. 1b, illustrates the *homogeneity accessibility bias* by contrasting two different cases. The one on the left depicts three individuals having access to the same destination. The one on the right shows three individuals belonging to different demographic groups having access to the same destination. These two cases are considered identical in terms of the number of individuals who have access to the same destination since in both cases each destination is accessible to three individuals. However, in the right case, d_1 is accessible by individuals from different demographic groups.



(a) Disparate destinations being accessible by distinct individuals is incorrectly equated with the same destination being accessible by different individuals.



(b) A destination being accessible by individuals from a homogeneous group is erroneously equated with a destination being accessible by individuals from different demographic groups.

Fig. 1. Isolation and Homogeneity accessibility biases.

A possible way to overcome these limitations is by employing a *time-geography* approach (Hägerstrand, 1970). In time geography, which constitutes the primary theoretical framework for conceptualizing person-based accessibility (Miller, 2005), an individual's accessibility is modeled using a space-time prism (Miller, 1991). The space-time prism represents the possible movements of an individual through both space and time, considering factors such as personal mobility constraints and time schedules (Song et al., 2017). The intersection of multiple individuals' space-time prisms across the continuous geographic space has been conceptualized through *joint accessibility* (Neutens et al., 2008; Farber et al., 2013, 2015).

In this work, we address the above-mentioned accessibility biases by proposing *co-accessibility* as a place-based measure that assesses a destination's potential to bring together different individuals and individuals from diverse demographic groups by being accessible to them. It considers spatial constraints without accounting for individual time constraints. This allows for its measurement without being hindered by the requirement for detailed data on the precise nature of an individual's (completed) activity patterns and trips, and the associated privacy and ethical concerns (Pirie, 1979; Lopes et al., 2019; Brum-Bastos and Paez, 2023). To address the *isolation accessibility bias*, the *co-accessibility* of a

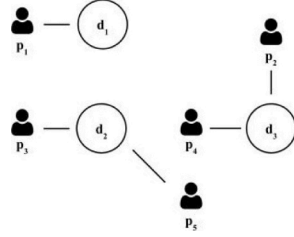
destination is determined by the number of individuals who have access to that destination. To address the *homogeneity accessibility bias* we need to consider the individuals' demographic groups and the *co-accessibility* of a destination is determined by the number of individuals who have access to that destination and the number of demographic groups these individuals belong to.

In Fig. 2, we present six dummy examples to illustrate how measuring accessibility and *co-accessibility* could enable us to examine the degree to which various destinations are accessible to different individuals and demographic groups. In all our examples we consider five individuals ($P_n = \{p_1, p_2, p_3, p_4, p_5\}$) and three destinations ($D_n = \{d_1, d_2, d_3\}$). Furthermore, in these examples, in alignment with the commonly found formulation of accessibility, for a destination to be considered accessible by an individual two conditions must be met: the individual needs to be able to reach the destination (low travel cost) and to consider the destination attractive (high destination attractiveness). To depict the accessibility of a destination by an individual, meaning that the individual can reach the destination and considers it attractive, we utilize lines that connect the individual to the corresponding destination.

The *co-accessibility* of a destination is indicated based on two numbers: the number of individuals who have access to that destination,

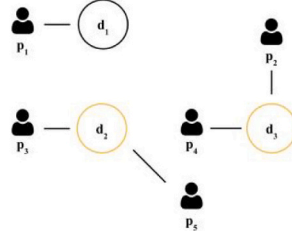
Accessibility & Co-accessibility

(I) Place-based Active Accessibility



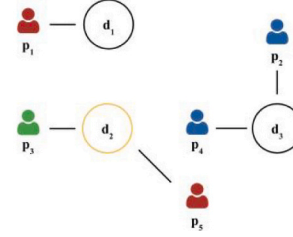
The distribution of destinations ensures that each individual has access to one destination. $d_1, d_2,$ and d_3 are considered equally accessible to different (groups of) individuals (Isolation and Homogeneity accessibility biases).

(II) Place-based Passive Accessibility



Destinations d_2 and d_3 are equally accessible to different individuals and more accessible than d_1 . Moreover, $d_1, d_2,$ and d_3 are considered equally accessible to different demographic groups (Homogeneity accessibility bias).

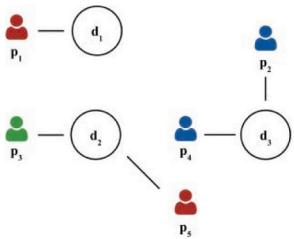
(III) Co-accessibility



Destinations d_2 and d_3 are equally accessible to different individuals. d_2 is also accessible to individuals belonging to different demographic groups (green and red in this example). d_1 and d_3 are not accessible to people from multiple demographic groups

Adjusting Co-accessibility

(IV) Individuals from different demographic groups



$$C = [\#\text{individuals}, \#\text{groups}]$$

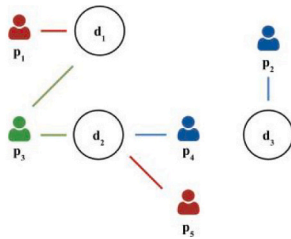
$$d_1 : C_{P_n}^{d_1} = [1,1]$$

$$d_2 : C_{P_n}^{d_2} = [2,2]$$

$$d_3 : C_{P_n}^{d_3} = [2,1]$$

Destination d_1 is not accessible to different individuals. d_2 is mutually accessible to two individuals and two demographic groups (green and red groups). d_3 is mutually accessible by two individuals and one demographic group.

(V) Individuals from different demographic groups (+) adjusting the travel cost per group



$$C = [\#\text{individuals}, \#\text{groups}]$$

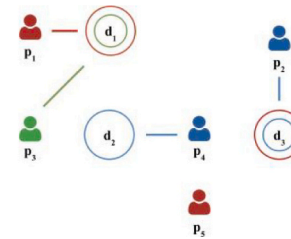
$$d_1 : C_{P_n}^{d_1} = [2,2]$$

$$d_2 : C_{P_n}^{d_2} = [3,3]$$

$$d_3 : C_{P_n}^{d_3} = [1,1]$$

This example demonstrates how adjusting the travel cost per group could alter the results of co-accessibility. In this case, d_1 is accessible to two individuals and two groups (red and green). d_2 shows the highest degree of accessibility since it is accessible to three individuals and all demographic groups under consideration (red, blue, and green). d_3 is only accessible to a single individual.

(VI) Individuals from different demographic groups (+) adjusting the destination attractiveness per group



$$C = [\#\text{individuals}, \#\text{groups}]$$

$$d_1 : C_{P_n}^{d_1} = [2,2]$$

$$d_2 : C_{P_n}^{d_2} = [1,1]$$

$$d_3 : C_{P_n}^{d_3} = [1,1]$$

This example demonstrates how further adjusting the destination attractiveness per group could alter the results of co-accessibility. For d_1 , the results remain the same: d_1 is accessible to two individuals and two groups. d_2 and d_3 are each accessible by only one individual and therefore exhibit a low degree of co-accessibility.

Fig. 2. Dummy examples used to illustrate how accessibility and co-accessibility measurements can indicate the degree to which different destinations are accessible to various individuals and demographic groups.

and the number of demographic groups to which the individuals with access to that destination belong. The purpose of these examples is to underscore the distinctions between the outcomes of (active or passive) accessibility and co-accessibility measures, and to demonstrate how co-accessibility could address the *isolation* and *homogeneity* accessibility biases presented in Fig. 1 a and b.

In examples (I) - (III) illustrated in Fig. 2, we examine the limitations of active and passive place-based accessibility measures towards

indicating the degree to which destinations are accessible to different (groups of) individuals. In example (I), following an active accessibility approach, each individual has access to one destination and all three destinations $d_1, d_2,$ and d_3 are considered to be equally accessible to different (groups of) individuals. In example (II), following a passive accessibility approach, destinations d_2 and d_3 are accessible to two individuals, while d_1 is accessible to only one individual. Moreover, destinations d_2 and d_3 are equally accessible to different individuals and

groups. In example (III), we illustrate the proposed co-accessibility measure, by extending passive accessibility to account for the different demographic groups. In this case, d_2 and d_3 are accessible to two individuals while d_1 is accessible to only one individual. When we further look at the demographic group of each individual, we also observe that only d_2 is accessible to individuals from different demographic groups (red and green) since d_1 and d_3 are accessible to only one group, red and blue respectively.

In examples (IV) — (VI) shown in Fig. 2, we demonstrate how further adjusting the co-accessibility measure could provide a more refined indication of the degree to which destinations are mutually accessible to different (groups of) individuals. Beginning with example (IV), similar to (III), destinations d_2 and d_3 are mutually accessible to two individuals while d_1 is accessible to only one individual. Looking at the number of groups who have access to each destination, we observe that d_2 is mutually accessible by two groups, while d_1 and d_3 are accessible by only one group. Thus, d_2 exhibits a higher degree of co-accessibility overall.

To measure the co-accessibility of a destination while considering the individuals' demographic groups, we also propose to account for the factors that impact the travel cost to reach it and are shared among the people of each demographic group (e.g., in the case of pedestrians belonging to different age groups we would need to consider the different walking speeds (Schimpl et al., 2011)). Certainly, within the same demographic group, individual differences still exist. Nonetheless, by tailoring the factors that impact accessibility by each population group, we gain a more nuanced understanding of co-accessibility compared to treating all groups as identical while avoiding the excessive complexity of considering each individual's unique preferences. In example (V), we adjust the travel cost per group to show how this consideration could alter co-accessibility. For instance, this adjustment could account for the differences in walking speeds, rather than assuming uniform speeds for all, by considering variations among children, adults, and the elderly. We illustrate the adjusted travel costs, using group-based colors for each line. In this case, the destination that shows the highest degree of co-accessibility is d_2 . d_2 is mutually accessible by three individuals all belonging to different groups. Then, d_1 follows, which is mutually accessible by two individuals, also belonging to different groups (red and green). Last is d_3 , a destination only accessible by a single individual.

Finally, we also account for the factors that impact the attractiveness of each destination and are shared among the people of each demographic group (Kitamura et al., 1997) (e.g., playgrounds are more attractive to children than to the elderly). In example (VI), we further adjust the destination attractiveness per group to show how this consideration could alter co-accessibility. We illustrate the adjusted destination attractiveness, using group-based colors for each destination. In this case, d_1 is mutually accessible by two individuals, also belonging to two different groups, and it is the destination with the highest degree of co-accessibility. Then, destinations d_2 and d_3 follow, each being accessible by only one individual.

3. Mathematical formulation of co-accessibility

In this section, we propose a mathematical formulation of co-accessibility. To measure the co-accessibility of a destination d for individuals from different demographic groups, we first need to measure the accessibility of d for each demographic group g . As illustrated in Fig. 2, this involves considering factors that influence the attractiveness of d and the travel costs associated with reaching it, which are assumed to be shared among members of each demographic group g . As mentioned in the previous section, individual distinctions persist even within the same demographic group. However, by adjusting the factors influencing accessibility for each group, we obtain a more nuanced understanding of co-accessibility compared to treating all groups as identical, while avoiding the excessive complexity associated with

considering the unique needs and preferences of each individual. Thus, within the formulation of co-accessibility, the travel cost depends on the location of the person $p_j \in g$ in relation to the destination d and on factors that impact traveling and are shared among the people who belong in group g (e.g., income level, available travel modes, walking speed, etc). Similarly, the attractiveness of a destination depends on factors that impact how attractive destination d is considered and are shared among the members of group g .

The passive accessibility of a destination d to n individuals who belong to the same demographic group g , allows us to address the *isolation accessibility bias* presented in Fig. 1a by expressing the degree to which d is mutually accessible by members of g and is formulated as:

$$c_g^d = h\left(A_{p_1}^d, A_{p_2}^d, \dots, A_{p_n}^d\right), \forall p_j \in g \quad (3)$$

where c_g^d denotes the (passive) accessibility of destination d to individuals from group g . $A_{p_j}^d$ is the accessibility of destination d to a person p_j from group g (Eq. 2). $A_{p_j}^d$ is determined by factors that impact how attractive a destination is considered and are shared among the people from group g , the location of the person in relation to the destination and factors that impact traveling and are shared among the people from group g . $A_{p_j}^d$ can adopt various types of accessibility measures depending on the underlying assumptions made, as explained by Levinson and Wu (2020). h represents a function that is used to aggregate the accessibility of destination d by each $p_j \in g$ and provides the co-accessibility of destination d by all individuals. We purposefully permit h to be non-linear and output different types of results such as single values (e.g., from summation) or distributions (e.g., from probability distribution functions). By embracing non-linearity in our approach, we aim to provide a versatile formulation that can yield a spectrum of results, catering to the demands of analyzing co-accessibility across different scenarios and contexts. For instance, h could be a summation and provide the total number of people who have access to a destination. This approach is commonly seen in passive accessibility measures (Lee and Salih, 2024; Lopes et al., 2019). When developing a co-accessibility measure, h can be tailored to account only for individuals belonging to a specific demographic group (e.g., the number of children with mutual access to a park). In that case, Eq. 2 can also be adjusted to the group under study. Alternatively, h could represent a probability distribution function, providing insights into the likelihood that individuals from demographic group g will access a destination. We refer to Eq. 3 as group-based co-accessibility, which essentially serves as a specialized passive accessibility measure.

Finally, the co-accessibility of a destination d to individuals belonging to a set of n mutually exclusive demographic groups G (e.g., [children, adults, older persons] or [low income, medium income, high income]), C_G^d allows us to address the *homogeneity accessibility bias* presented in Fig. 1b and can be formulated as:

$$C_G^d = H\left(c_{g_1}^d, c_{g_2}^d, \dots, c_{g_n}^d\right), \forall g_i \in G \quad (4)$$

where H is the function used to aggregate the co-accessibility values of destination d for each group in G , resulting in the overall co-accessibility of the destination for all groups in G . Like h , the selection of H

depends on the context of the problem being studied. H aims to address the homogeneity bias and allows for the differentiation of destinations based on their accessibility to individuals from different demographic groups. Therefore, H can be chosen to reflect the diversity of the people who have access to a destination according to their demographic group. Examples of widely known diversity indices that can be used include Shannon's Equitability Index (Shannon, 1948), Simpson's Diversity Index (Simpson, 1949), and the Gini Index (Gini, 1912). Alternatively, for simplicity, H could be a summation reflecting the number of different demographic groups with access to d .

4. Sample case study

We employ a representative case study to demonstrate how the proposed co-accessibility measure can be compared with and complement the more commonly used active accessibility measures. The simplified co-accessibility measure we use does not encompass all the factors influencing co-accessibility as discussed in earlier sections. Its aim is to facilitate a discussion on the applicability of co-accessibility and to highlight the intricacies and challenges involved in its measurement.

Our case study is defined by four key aspects: the area of analysis, the travel mode, the demographic attributes, and the type of destinations involved. The area of analysis is the city of Amsterdam in the Netherlands. We chose Amsterdam due to its diverse array of neighborhoods, which include both historic and more recently developed areas. Additionally, Amsterdam features a mix of pedestrian-friendly streets and barriers, such as canals and high-traffic roads. As for the travel mode, our focus is on pedestrians. Walking is chosen as it is the most affordable and accessible travel mode for individuals of virtually every population group, it is a sustainable means of transport, and it has been shown to positively contribute to people's well-being. The demographic characteristic we examine is age. The need for urban spaces that bring people of different ages together and encourage intergenerational encounters is universal and relevant to most countries and cities, as underscored by the United Nations' Sustainable Development Goal 11.7 (UN General Assembly, 2015). The selection of destinations is guided by the concept of *third places* introduced by Oldenburg (1989), encompassing venues where individuals of different ages can encounter each other beyond the realms of home and work. Specifically, we selected destinations that are accessible to individuals of all ages, such as parks, playgrounds, and museums while deliberately excluding venues that impose age restrictions to access, such as casinos or nightclubs.

4.1. Measuring accessibility & co-accessibility

To assess accessibility and co-accessibility, we employ an isochrone-based measure. Isochrones show what destinations can be reached from an origin location within a given travel cost threshold (El-Geneidy and Levinson, 2007; Levinson and Wu, 2020). Isochrones are selected because of their simplicity and ease of interpretation, characteristics that also contribute to their widespread adoption by practitioners (O'Sullivan et al., 2000).

We make three main assumptions. First, we consider all destinations in our analysis equally attractive to all groups. Second, we assume all people walk at the same speed: 1.26 m/s (i.e., the average of different age groups, as measured by Schimpl et al. (2011)). The reason for not adjusting the walking speed per age group is that considering the lowest (1.2 m/s) and highest (1.29 m/s) average walking speeds found by Schimpl et al. (2011) would only result in a difference of 81 m within a 15-min walk. This difference cannot be reflected in our estimations due to the spatial resolution of the employed population data (100 × 100m grid cells). Third, regarding the travel cost we only account for the walking time and consider accessible every location a person can reach within a 15-min walk from their home. We opted for the 15-min walking distance threshold because it is increasingly utilized both in research and in practice, with several cities integrating it into their urban planning strategies in recent years (Weng et al., 2019; Willsher, 2020; Moreno et al., 2021; Pozoukidou and Chatziyiannaki, 2021; Caselli et al., 2022). However, we acknowledge that assigning any time threshold is somewhat arbitrary in nature. Based on these three assumptions, the accessibility of a destination d by an individual $p_j \in g$ is formulated as:

$$A_{p_j}^d = \begin{cases} 1 & \text{if walking - time between } d \text{ and } p_j \leq 15 \text{ minutes} \\ 0 & \text{if walking - time between } d \text{ and } p_j \geq 15 \text{ minutes} \end{cases} \quad (5)$$

To identify which destinations are accessible to each individual, we model the pedestrian street network as a graph, with nodes representing street intersections and edges representing street segments. We then overlay a grid layer (100 × 100m) indicating residential areas and determine the closest intersection to the center of each grid cell. These intersections represent individuals' home locations. Next, we calculate 15-min walking trips from these home locations, considering the length of each street segment and the average walking speed defined earlier. This process allows us to measure all destinations within the reach of these walking trips for each individual.

To measure the co-accessibility of a destination by a particular group we need to define the function h as shown in Eq. 3. In our analysis, we define h as a summation to align with the aforementioned isochrone-based measurement of accessibility. Thus, the group-based co-accessibility of a destination by the n individuals from group g is formulated as:

$$c_g^d = \sum_{j=1}^n A_{p_j}^d, \forall p_j \in g \quad (6)$$

After having calculated the co-accessibility of destinations per group we can calculate the co-accessibility of each destination by all groups. To do so, we need to define the function denoted as H in eq. 4. In our case, we are interested in the degree to which a destination is mutually accessible by a set G of n different age groups (g_1 is children, g_2 is adults, g_3 is elderly). Therefore, H is chosen to represent the age diversity of the people who can access each destination by means of Shannon's Equitability Index (Shannon, 1948). Shannon's Index is selected as it is among the most commonly used diversity indices and summarizes in a single number a partial description of species richness and evenness (Daly et al., 2018; Mendes et al., 2008). Thus, Eq. 4 is now:

$$C_G^d = \frac{-\sum_{i=1}^n P_{g_i}^d \times \ln P_{g_i}^d}{\ln(n)}, \forall g_i \in G \quad (7)$$

where $P_{g_i}^d$ is the ratio of the co-accessibility of d by each age group ($c_{g_i}^d$) over the total number of individuals with access to d ($\sum_{i=1}^n c_{g_i}^d$); n is the count of age categories. The C_G^d values range from 0 to 1, with 1 indicating a perfect balance in the proportions of each age category.

4.2. Data

We use three different types of data: population demographics, pedestrian street network data, and location-based data. Starting with the population demographics, to collect information reflecting peoples' residence location and age we use the Dutch *Centraal Bureau voor de Statistiek* (2020) (spatial resolution of 100 × 100m). The collected data pertain to the year 2020. In total, the population demographics data include 6949 grid cells reflecting the entire Amsterdam. We group residents into three population age categories: *children* (0–15 years old), *adolescents and adults* (16–64 years old), and the *elderly* (equal or above 65 years of age).

The data related to the pedestrian network reflect streets that are considered for pedestrians such as sidewalks and pedestrianized streets. We obtain this information from *OpenStreetMap* (2021), by collecting the streets for which the *network_type* is set to “walk” using the *OSMNx* package (Boeing, 2017). Thus, we only collect streets for pedestrians and exclude streets such as motorways, bike lanes, or service roads. The street network of *OpenStreetMap* has been determined to be approximately 83 % complete in over 40 % of countries worldwide (Barrington-Leigh and Millard-Ball, 2017). When focusing on the pedestrian street network studies have suggested that *OpenStreetMap* data provide a free and adequate alternative in situations where commercial pedestrian data sets are not available (Zielstra and Hochmair, 2012). The data collection was realized in November 2021. The collected street segments

lie within the administrative boundaries of Amsterdam, as delineated from the open Dutch land use dataset Basisregistratie Grootchalige Topografie (BGT) (Kadaster, 2020), extended by a buffer of 1 km to minimize potential boundary effects (Hillier et al., 1993).

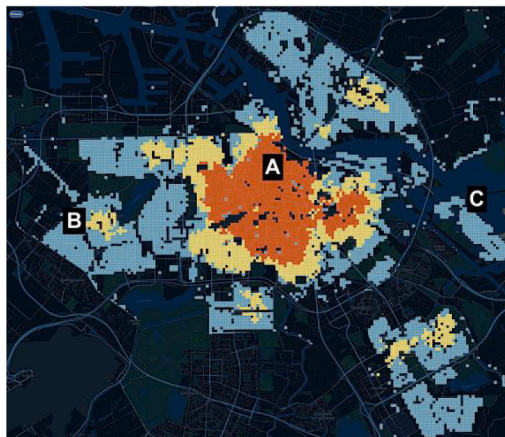
Lastly, the locations are also collected from OpenStreetMap. In particular, we select and collect locations that lie within the administrative city boundaries of Amsterdam extended by a buffer of 1 km and come from the following primary feature groups: *Amenity*, *Entertainment*, *Arts & Culture*, *Leisure*, or *Shop*. OpenStreetMap has been considered a valid source for such data with an acceptable level of completeness (Zhang and Pfoser, 2019; Koukoletsos et al., 2012; Logan et al., 2021). The data collection process was realized in September 2021. In total, we collected 10,483 locations.

4.3. Results

The results of the measurements of pedestrian accessibility and co-accessibility are illustrated over three types of maps. First, the maps of pedestrian (active) accessibility highlight the number of destinations accessible from each grid cell within a 15-min walk. According to Eq. 5, these maps show the total number of accessible destinations for each grid cell included in our analysis. Second, the maps of pedestrian co-accessibility per group (c_g^d) (passive accessibility) display the total number of people within a specific age group who can access a destination, estimated using Eq. 6. Third, the maps of the co-accessibility of each destination from all groups (C_G^d) reflect the age diversity of the people with access to each destination, as calculated through Eq. 7.

For the visualizations, we first calculate the average accessibility of

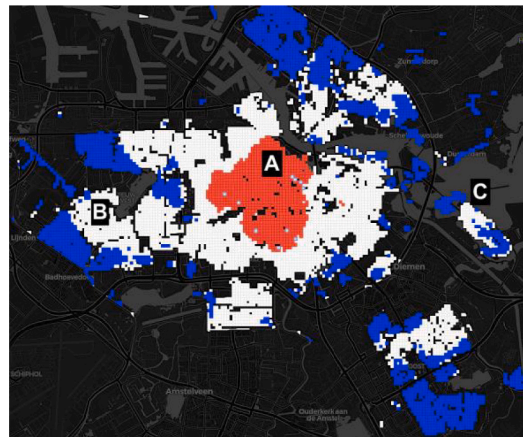
(a) Accessibility of destinations from each grid cell within a 15-minute walk.



Number of accessible destinations within a 15-minute walk from each grid cell.

- Higher than average (> 340)
- Near-average (240 ± 100)
- Lower than average (< 140)

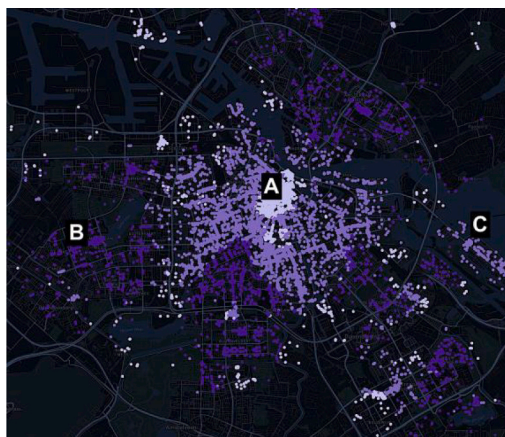
(b) Local spatial autocorrelation (Moran's I) of the number of accessible destinations from each grid cell within a 15-minute walk.



Number of accessible destinations within a 15-minute walk from each grid cell.

- High values
- Not significant
- Low values

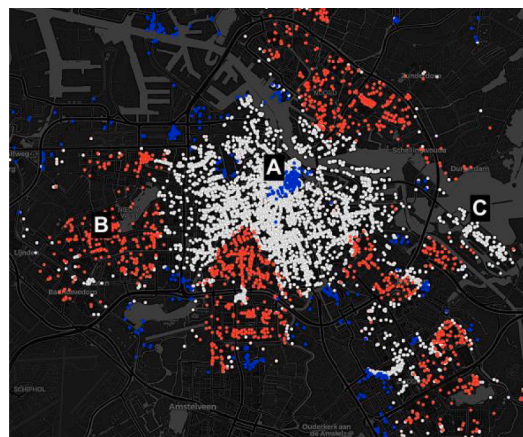
(c) Co-accessibility of each destination based on the age diversity of the people who have access to it within a 15-minute walk.



Destinations' age diversity based on the individuals who have access to them within a 15-minute walk.

- Higher than average (> 0.66)
- Near-average (0.61 ± 0.05)
- Lower than average (< 0.56)

(d) Local spatial autocorrelation of the age diversity of the people who have access to each destination within a 15-minute walk (Moran's I).



Destinations' age diversity based on the individuals who have access to them within a 15-minute walk.

- High values
- Not significant
- Low values

Fig. 3. Accessibility and co-accessibility (based on age diversity) of different areas in Amsterdam.

all grid cells and the average co-accessibility of all destinations. Then we cluster our values in three groups and color them accordingly: *Higher than average*, *Near-average*, and *Lower than average*. To identify the statistically significant clusters of high and low values we further create a connectivity matrix using queen contiguity-based spatial weights and measure the spatial autocorrelation using Moran's I correlation coefficient.

4.4. Comparison of accessibility and co-accessibility

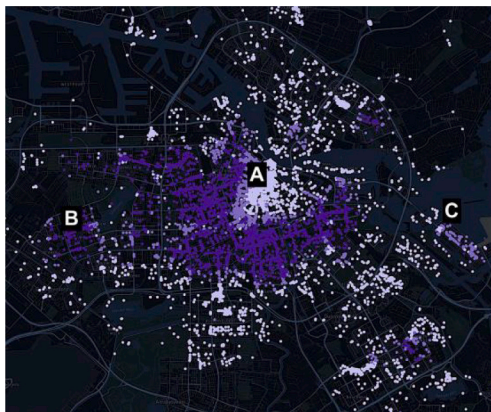
We display our area-based results through Figs. 3 and 4. Panels 3a and 3b highlight the spatial inequities in accessibility. In particular, panel 3a shows the number of accessible destinations within a 15-min walk from each grid cell and 3b further underpins the spatial clusters of grid cells with a significantly high (or low) number of accessible destinations, compared to the mean. Then, panels 3c and 3d present the destinations' co-accessibility in terms of how age-diverse is the set of people who have access to each destination. Fig. 4 follows the same structure while focusing on the accessibility and co-accessibility of different areas per age group (i.e., children and elderly).

As indicative examples, we consider three areas denoted as A, B, and C. People residing in area A have access to the highest number of destinations in comparison to any other area. Indicatively, people in the vicinity of A have access to a significantly high number of destinations compared to other areas, as can be seen from panel 3b, ranging from around 2250 to 400.

Regarding co-accessibility, the destinations located in area A are accessible within a 15-min walk by a significantly low or near average in terms of age-diversity set of people compared to other destinations as depicted in panels 3c and 3d. These results are also supported when looking at the group-based co-accessibility (panels 4a–d): the destinations within the A area are accessible by a significantly lower number of children, compared to the mean. Thus, by comparing the results of accessibility and co-accessibility for the area A we see that a higher number of accessible destinations does not directly translate to a higher number of destinations that are simultaneously accessible by multiple age groups.

The people residing within the B area, have access to a more limited range of destinations typically varying between 10 and 180. In certain cases, the number of accessible destinations is statistically significantly

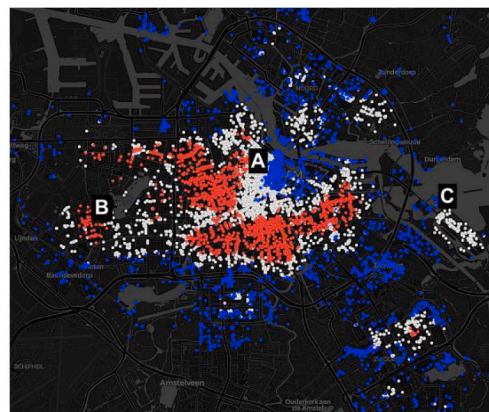
(a) Co-accessibility of each destination based on the number of children who have access to it within a 15-minute walk.



Number of children who have access to each destination within a 15-minute walk.

- Higher than average (> 2865)
- Near-average (2365 ± 500)
- Lower than average (< 1865)

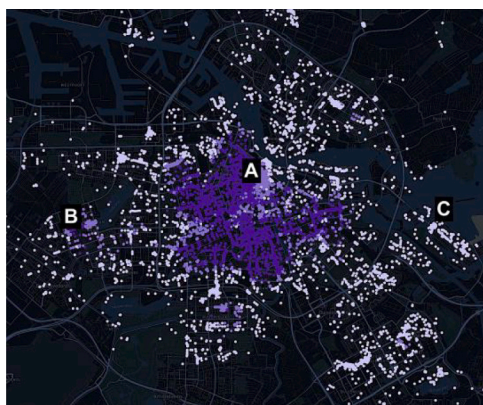
(b) Local spatial autocorrelation of the number of children who have access to each destination within a 15-minute walk (Moran's I).



Number of children who have access to each destination within a 15-minute walk.

- High values
- Not significant
- Low values

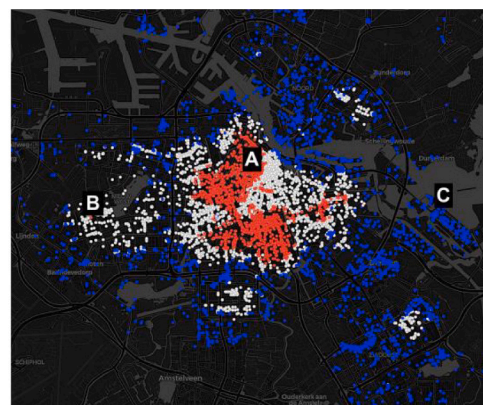
(c) Co-accessibility of each destination based on the number of elderly people who have access to it within a 15-minute walk.



Number of elderly people who have access to each destination within a 15-minute walk.

- Higher than average (> 3378)
- Near-average (2878 ± 500)
- Lower than average (< 2378)

(d) Local spatial autocorrelation of the number of elderly people who have access to each destination within a 15-minute walk (Moran's I).



Number of elderly people who have access to each destination within a 15-minute walk.

- High values
- Not significant
- Low values

Fig. 4. Accessibility and co-accessibility (based on children and elderly) of different areas in Amsterdam.

lower than the mean, as indicated by panel 3b. Regarding co-accessibility, the destinations within area *B* are mutually accessible by a significantly broader age range of people compared to other destinations. Regarding the number of children who have access to the destinations in that area, we can observe diverse results with small clusters of destinations that are accessible to either a near-average or significantly higher number of children. When looking at the elderly, we see results that are closer to the mean.

Similarly to the *B* area, the people residing within the *C* area have access to a statistically significantly lower number of destinations, compared to the mean, as shown in panel 3b. When looking at co-accessibility, the estimated age diversity values of the destinations within area *C* are not significantly higher or lower than those of other destinations. However, when focusing on specific groups we observe that the destinations within the *C* area, are found to be accessible by a significantly low number of elderly.

In summary, the results of accessibility and co-accessibility provide complementary insights. While accessibility provides information regarding the extent to which destinations are accessible to people, co-accessibility indicates the degree to which the destinations of each area promote encounters among individuals belonging to the same age group (tackling the *isolation accessibility bias*) or different age groups (tackling the *homogeneity accessibility bias*) by being accessible to them.

5. Discussion and conclusion

This work lays the groundwork for a methodological framework for measuring co-accessibility, which assesses the degree to which various destinations are mutually accessible to individuals from different demographic groups. We demonstrated how a measure of co-accessibility could enhance traditional accessibility metrics and alleviate inherent biases such as the *isolation* and *homogeneity* bias. We also outlined the components of co-accessibility and proposed a mathematical formulation for its measurement. In the following paragraphs, we highlight potential opportunities and prospective measurement challenges to support future research endeavors in related fields.

Co-accessibility is a place-based measure that shares some conceptual similarities with passive accessibility and other person-based measures such as joint accessibility. The advantage of person-based measures is that they consider both spatial and time constraints. However, their implementation in real-world case studies can be challenging due to the need for detailed data on individual spatiotemporal activity patterns. Additionally, it is cumbersome to apply such measures when evaluating future spatial planning interventions since they rely on data from past activities and trips. These challenges have been well-documented in the literature (Pred, 1977; Pirie, 1979). Co-accessibility offers an alternative for examining how mutually accessible destinations are to different individuals and demographic groups when detailed data cannot be collected due to time or monetary costs or should not be collected because of ethical concerns.

We introduced co-accessibility as a broad concept but subsequently narrowed our focus to measure and apply it in a sample case study. Specifically, we measured co-accessibility by focusing on a single mode of travel, namely walking, and a given demographic, namely age. Nevertheless, co-accessibility can be applied across any mode of travel or demographic group. For instance, when considering other demographic groups, co-accessibility could be valuable for studying segregation phenomena, typically centered on ethnicity (Reardon and O'Sullivan, 2004), income (Vaughan and Arbaci, 2011), or education level (Gordon and Monastiriotis, 2006) by enabling to go beyond the commonly studied domains of residential (Charles, 2003), workplace (Hellerstein and Neumark, 2008), and educational settings (Frankel and Volij, 2011).

Similarly, measures of co-accessibility could be employed to compare the effectiveness of public transportation systems in fostering place-based encounters. Such an examination could delve into

understanding how considering different modes of travel, such as public transportation, private vehicles, or cycling impacts co-accessibility. This approach could provide insights into the social dynamics facilitated by different transportation modes and expand existing research on the impact of public transport on social encounters (Lyons and Chatterjee, 2008; Bissell, 2016).

Moreover, measures of co-accessibility can be leveraged to guide the design of destinations to better meet the wants and needs of those who can reach them. This approach can help to address issues of spatial inequality and spatial justice by ensuring equitable access to essential services and opportunities for all demographic groups. Studying the co-accessibility across different destinations might also provide a nuanced understanding not only of the capacity of destinations to facilitate encounters among diverse individuals but also of the intrinsic characteristics of areas that nurture this potential. These characteristics extend to the surroundings of the destinations which, as Jane Jacobs argued, can generate mutual support and “complex pools of use” that encourage people to use destinations at different times of the day (Jacobs, 1961; Talen, 2010). Additionally, prospective interventions or urban design scenarios can be converted into input data for the proposed measure to assess their impacts on co-accessibility. However, this undertaking must be approached with caution, as there is a risk of developing urban destinations tailored to the predominant population groups that have access to them, inadvertently marginalizing other population subgroups (Rishbeth, 2001).

Lastly, our sample case study highlighted the complexities associated with the measurement of co-accessibility, revealing inherent challenges that should be addressed. We identify three main challenges for measuring co-accessibility. The first challenge stems from the necessity to identify and measure the factors influencing accessibility for various demographic groups. This is illustrated through examples (IV)-(VI) in Fig. 2, where we adjust the travel cost and destination attractiveness per group. While it is important to account for demographic disparities, it is challenging to simultaneously identify and measure such differences in a time and cost-effective manner. The factors that influence accessibility are group-specific, many, and intertwined (Gargiulo et al., 2018; Merlin et al., 2021). As a result, there is the challenging task of disentangling the impact of each factor and prioritizing them for the different groups. Moreover, some factors can be very subjective and thus difficult to capture, particularly when adjusting for the different demographic groups. For instance, when considering pedestrian co-accessibility, such factors can be the perceived safety or the attractiveness of a street which can influence whether a person can walk to a destination (Ewing and Handy, 2009; Miliás et al., 2023).

Second, the proposed mathematical formulation of co-accessibility (expressed through Eq. 3 and 4) is purposefully quite broad, encompassing more of a conceptual formulation, aiming to guide and inspire the development of new context-specific co-accessibility measures, rather than a “ready-to-follow” recipe one can use to measure co-accessibility. To apply a co-accessibility measure three main questions need to be answered first: How to measure accessibility (Eq. 2)? How to aggregate the accessibility of a destination to different individuals belonging to the same group (Eq. 3)? How to aggregate the co-accessibility of a destination to multiple groups (Eq. 4)? Establishing a consistent selection process protocol for defining these functions proves challenging, as this decision is influenced by a variety of factors such as the context (e.g., demographics), the data availability, and the specific aspect of the problem under investigation (e.g., assessing co-accessibility statically or dynamically based on time, season, or weather). In this quest, other scientific fields can provide valuable insights. For instance, the plethora of accessibility studies can aid the selection of the most relevant accessibility measure to the problem under study. In another example, when selecting aggregation functions to measure the diversity of individuals with respect to their demographic traits, one can draw insights from existing studies on the potential and limitations of different diversity indices (DeJong, 1975).

Third, when measuring co-accessibility, it is important to consider the interplay between a destination's co-accessibility and visitation patterns. This relationship may indicate how to assess co-accessibility to better reflect its impact on real visitation patterns. The influence of co-accessibility on visitation patterns can be complex and may exhibit variations based on demographics, cultural nuances, time, or season. Relevant literature on visitation patterns can provide valuable guidance on how to approach this relationship (Schläpfer et al., 2021; Xiao et al., 2018). The aforementioned opportunities and challenges serve as avenues for additional investigation and hold the potential to shape the trajectory of future research endeavors that expand upon the concept of co-accessibility.

CRedit authorship contribution statement

Vasileios Miliás: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Achilleas Psyllidis:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Alessandro Bozzon:** Supervision, Funding acquisition.

Declaration of competing interest

The author(s) declare no potential conflicts of interest.

Data availability

Data will be made available on request.

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