Urban Networks Special Issue: AGGREGATED SOCIAL ACCESSIBILITY

Predicting accessibility of walking attractors based on the configuration and pedestrian movement potential of street network

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Keywords
Street network, Centrality, Accessibility, Walkability, Walk Score,

Abstract

A common approach to evaluating the quality of urban environments in terms of walkability is to measure the accessibility of walking attractors. However, this approach is of little use when trying to evaluate the quality of future environments during the planning process simply because the necessary data is not available at this stage. By addressing this deficiency, our goal with this paper is to predict the long-term impact of planning decisions about the street network configuration on the accessibility of walking attractors (AWA).

The theoretical model presented in this paper is based on the hypothesis that street network configuration influences how people move through space, and this in turn affects the allocation and accessibility of walking attractors. We empirically test this hypothesis in a case study of Weimar, Germany and found that street network configuration alone was significant and the strongest predictor of AWA. We show how street network influences the distribution of people in terms of movement flows and that the access to these movement flows is highly correlated to the neighborhood walkability. This highlights the importance of urban structure as an interface for social interaction and suggests the positive effect of social proximity on the quality of environment.

Introduction

Why do we move from one place to another, and how do we decide where to go, settle down and spend our lives? The process of leaving one location in favour of another, more suitable for living, is determined by our ability to evaluate the quality of an environment. The critical decision about where to live can be expressed and measured in terms of opportunities offered by the environment. In doing so, we consider the attractiveness of opportunities and the effort necessary to access them (Tobler 1970). The key term expressing this intuitive and widely established concept in the field of geography is accessibility, which combines both the attractiveness and the proximity of the opportunities (Batty 2009).

Based on this concept, many variations of accessibility-based measures of environmental quality have been developed, differing mostly in the definition of the opportunity which is being accessed. Depending on the social, economic or cultural context, it might be access to drinking water (Yang et al. 2013), to healthcare (Luo & Wang 2003) or jobs (Hu 2013). One specific group of accessibility measures based on quantifying the access to walkability attractors (AWA) has gained increasing attention in recent years. Due to several online tools providing the assessment of AWA (e.g. Walk Score, Walkshed) it became arguably one of the mostly widely applied environmental quality assessment methods accounting for more than 20 million evaluations per day (walkscore.com). In general, the AWA assessment is based on a) defining walking attractors[1] b) geo-locating the walking attractors and c) measuring the distance to walking attractors. The advantage of this method is that after walking attractors have been defined, the rest of the procedure can be automated[2] and easily calculated for a great number of locations. The relevance of AWA has been empirically tested and supported by a growing number of studies showing its relation to physical activity, walking behaviour and health indicators (Hirsch et al. 2013; Brown et al. 2013; Duncan et al. 2016; Chiu et al. 2015).

Moreover, AWA has proved to be a good proxy of qualitative indicators of walkability (aesthetics, presence of sidewalks etc.), which is especially important since these, in contrast to AWA, are not available in standardised electronic form and have to be collected manually at high cost (Koschinsky et al. 2016). Another key point supporting these findings and the general validity of AWA as a measure of environmental quality is the fact that it has been associated with its economic expression – the real estate value (Pivo and Fisher 2011). As shown by Pivo and Fisher (2011), the value of 10 Walk Score

[1] Walking attractors are considered on the level of an individual or are aggregated on a group of people/population

[2] Locations of specific functions and land uses could be automatically acquired from open geo databases such as Google Maps, Education.com, Open Street Map, the US Census and Localeze

points was associated with up to a 9% increase in the property value, depending on the property type.

Despite the obvious benefits of AWA for evaluating existing environments, it is of little use in planning processes where decisions with long term impact are made. We argue that in the context of the current global urbanisation rate – with more than half the world's population living in cities, a proportion that is expected to rise to two-thirds by 2050 (UN 2014) – the evaluation of future environments becomes of primary concern. However, when trying to evaluate the environmental quality of a new district or city during the planning stage, the application of AWA fails simply because the allocations of most of the walking attractors are not known at this stage. Additionally, even if these were explicitly planned, they are prone to the internal dynamics of urban systems and tend to adapt to the long-term potentials given by the urban form (Al Sayed & Penn 2016; Banister et al. 1998; Hillier et al. 1993; Penn et al. 1998). In other words, the influence of planning on the allocation of specific functions by creating incentives and morphological potentials is rather indirect and therefore hardly foreseeable. As a result, the evaluation of walkability is currently only the subject of post-hoc measurement and is limited to describing the quality of the existing environments.

Research question, hypothesis and limitations

In order to actively plan for future walkable environments, the question addressed by this research is about the of long-term planning decisions on the distribution and accessibility of walking attractors. We specifically focus on measuring the relationship between the street network configuration on AWA. We consider this as particularly important since not only the streets themselves are "long-lasting constituent elements of urban form" (Marshall 2006), but also their configurational properties remain stable over the time – in other words, the central streets with high connectivity remain central and well connected throughout the process of urban evolution (e.g. expansion, densification) (Strano et al. 2012; Barrington-Leigh & Millard-Ball 2015). Therefore, the ability to predict the long-term effect of street network configuration on AWA is a crucial precondition of planning processes oriented towards walkable neighbourhoods.

The predictive model of AWA introduced and empirically tested in this paper is based on the research hypothesis that a) street network configuration influences how people move through space and b) that these movement flows affect the allocation and accessibility of walking attractors.

It must be noted that in this research we limit our method to prediction of aggregated AWA. As previously mentioned, this is based on defining the walking attractors aggregated to the population as opposed to considering the individual preferences. We consider the aggregated approach more applicable for the planning of new environments as the individual needs and preferences of the future inhabitants are not known at this stage. This could be considered as limitation of our approach since the socio-demographic characteristics of individual households influences the relationship between AWA and the actual observed travel behaviour (Manaugh & El-Geneidy 2011). However, we argue that the aggregated approach can still meaningfully inform planning, since the individual characteristics affects the strength of the AWA's impact on walking behaviour, but its direction remains the same. In other words, neighbourhoods with higher AWA will increase the walking behaviour of its inhabitants, but the magnitude of the increase might depend on their socio-demographic characteristics.

Aggregated Social Accessibility Method

In accordance with our research hypothesis, we present a two-step method for predicting the AWA based on the street network configuration. First, we adopt an established graph centrality measure *Betweenness* to estimate the human movement flows based on the configurational properties of the street network. The novelty of the presented method is that in second step, we measure the accessibility of the predicted movement flows. Since the movement and the accessibility to people is central to our method, we termed it Aggregated[3] Social Accessibility (ASA). As show in Figure 1, we assume that the distribution of movement flows is related to the distribution of walking attractors. Consequently, we expect the accessibility to movement flows (ASA) to be closely related to accessibility to walking attractors (AWA).

[3] The aggregation illustrates that the accessibility is not measured between specific individuals but as an aggregation to the whole population represented in terms of "movement flows"

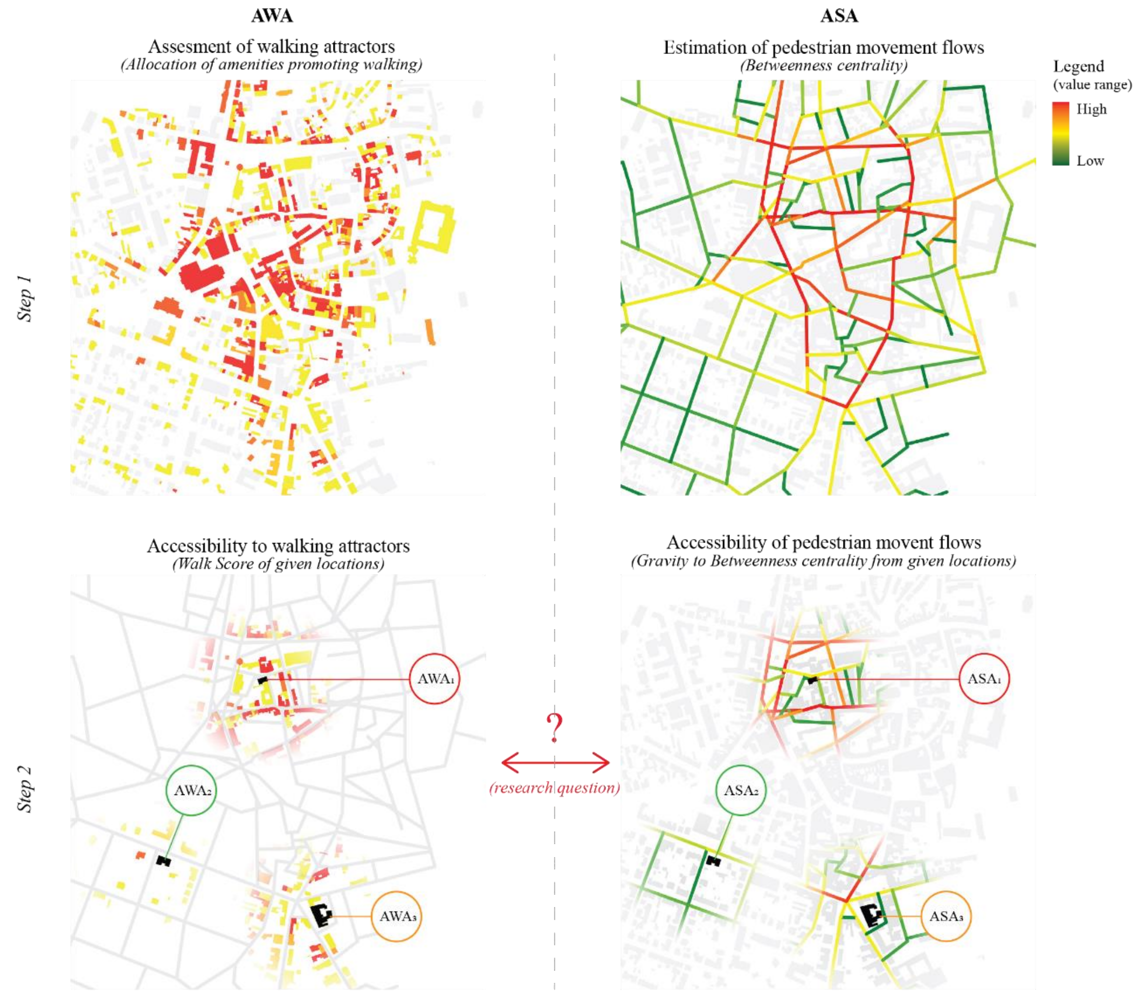

Figure 1. Conceptual scheme illustrating the research question and method

We limit our model to the distribution of pedestrian flows as, compared to other means of transport, these have unique qualities, namely the ability to interact with their immediate surroundings (Gehl 1987). This is of special importance since the relationship between the distribution of people and walking attractors can be established only if the attractors and people can interact and therefore benefit from each other.

Part 1: Street network centrality as a predictor of pedestrian flow

Methods for modeling pedestrian flow depend highly on the data available as model input. In general, the aggregation and the level of detail of the model are closely related, meaning that detailed prediction on the level of the individual requires detailed data about the individuals and their environment (Voorde 2011). The model developed in this research aims to reveal the long-term impact of early planning stages and therefore limits the input data to street network.

For this reason, the *Space Syntax* method is adopted as an established approach to assessing the impact of spatial configurations on different behavioural phenomena, such as the allocation of functions or movement flows (Hillier et al. 1993). As argued by *Space Syntax* scholars, this analytical framework is able to explain 60% to 80% of variance in movement rates as an effect solely of the street network, ignoring all other environmental variables (Penn 2003). While the simplicity and the explanatory power of *Space Syntax* has been identified as a major advantage of the method, several implicit assumptions about the environment must hold true for its predictive power to be valid: It is assumed that movement attractors are either evenly distributed throughout the network or follow the pattern of movement network configuration as a multiplier of its natural potential (Hillier 1999, p. 176; Hillier et al. 1993, p. 31). These assumptions might be perfectly reasonable in emergent, unregulated urban systems if the network configuration and land use have the necessary freedom and time to harmonise. However, evidence shows that even in the cases of planned cities, the density and land use patterns tend to adapt to the potentials given by the street network configuration (Al Sayed & Penn 2016).

The *Space Syntax* approach to analysing urban systems is based on the idea of visual axes as movement trajectories and their relationships represented as the dual of a spatial graph (Hillier & Hanson 1984). This representation makes it possible to apply graph-theoretical measures to evaluate and quantify the relationships of each spatial element to the whole system. From the vast opportunities offered by *Space Syntax'* analytical framework, one specific model introduced by Turner (2001) as an "angular segment map" seems to be a particularly strong predictor of pedestrian movement in the urban context (Hillier & Iida 2005; Turner & Dalton 2005; Varoudis et al. 2014). This spatial graph consists of vertices as visual axes divided at their intersections (segments) and their connections as edges weighted by the angular deviation between the adjacent segments (see Figure 2). The segment map can also be seen as a special case of a street network graph[4] with intersections modelled in a way that can be used to approximate human movement by

[4] The movement network considered in Space Syntax analysis is an extension of the street network. All accessible public space is connected through movement network including special multi-level connections such as tunnels, skywalk etc.

minimising angular turns along a path. Consequently, the unit of distance between a pair of nodes is expressed as an angular deviation as opposed to the traditional temporal, metric or topography[5] based approaches rooted in geography. As a matter of fact, topological or angular distance as a specific feature of the *Space Syntax* model, has been repeatedly confirmed to be a better predictor of pedestrian and vehicular movement compared to its metric counterpart (Hillier & Iida 2005; Lerman et al. 2014).

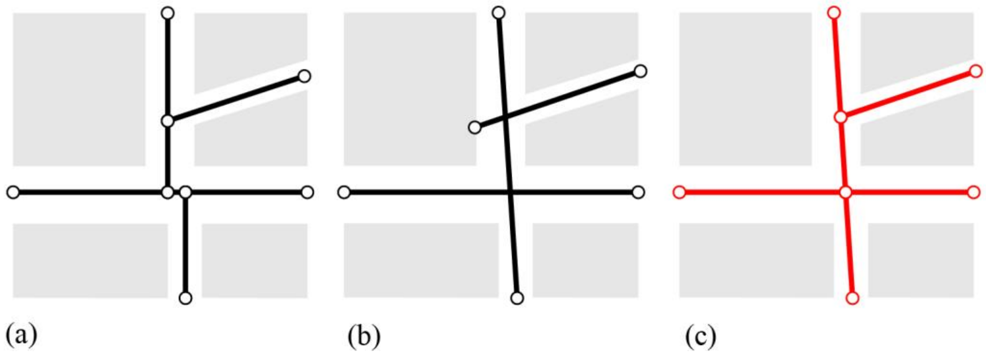

Figure 2. Various spatial network representations (a) Street center line (b) Axial map (c) Segment map

The prediction is based on the importance of individual segments in terms of their network centrality. A specific type of centrality used to estimate the impact of a street network's configuration on movement was introduced by Freeman (1977) under the term *Betweenness* as a measure of the information flow in social networks. Later, it was adopted by geographers and *Space Syntax* scholars as a measure of traffic flow in spatial networks. The *Betweenness* centrality of node i in a street network is defined as the sum of all possible shortest paths that traverse through i. Formally, *Betweenness* of a node is expressed as:

$$Betweenness[i]^r = \sum_{j,k \in G-\{i\}, d[j,k] \leq r}^{N} \frac{n_{jk}[i]}{n_{jk}} \tag{1}$$

where N is the number of nodes in the system, n_{jk} is the number of shortest paths between nodes j and k, and $n_{jk}[i]$ is the number of these shortest paths that pass through the node i.

[5] The movement network is considered as a two-dimensional projection with no information about the slope of a street segment. This may reduce the predictive power of the model in urban structures with high variation in elevation.

The definition of travel radius r is crucial, since it reflects the maximum travel distance and therefore the different travel modes. *"Within transportation planning, a quarter-mile (400 m) is often used as a rule of thumb for the walkable catchment area of an opportunity"* (Vale & Pereira 2016), however various studies suggest a high variance in maximal walkable distance and a clear need for empirical calibration of this parameter as discussed in the following section.

Part 2: Accessibility to pedestrian flow as predictor of AWA

Conceptually, the ASA approach follows the logic of the AWA with the main difference that instead of walking attractors, the accessibility of people is being considered. In order to measure access to people, their distribution represented as pedestrian movement flows has been estimated based on a street network's *Betweenness* centrality.

The concept of accessibility *"is often seen as a measure of the cost of getting from one place to another, traded off against the benefits received once the place is reached"* (Batty 2009). Formally, it has been denoted by Hansen (1954) as a gravity function proportional to the attractiveness of all locations j surrounding i and inversely proportional to travel cost between i and j (Equation 2).

$$Gravity[i]^r = \sum_{j \in G - \{i\}, d[i,j] \leq r} \frac{W[j]}{e^{\beta . d[i,j]}} \tag{2}$$

Of fundamental importance in the Gravity function is the definition of travel cost – the impedance function, as it can take many forms, defining the inconvenience to travel based on the travel distance between origin and destination (Vale & Pereira 2016). The method used most often, closely tied with travel behaviour theory, is the negative exponential form of the impedance function (Handy & Niemeier 1997). The ASA method adopts this function with the distance-decay parameter β set to 0.00217[6] as empirically calibrated by Handy & Niemeier (1997).

In the adopted gravity function as a measure of accessibility, the weight W of a destination j is based on the movement flow potential of the street network given by the angular shortest path *Betweenness* centrality calculated in the first step. The movement potential of an individual street segment is discretised and mapped to points representing destination vertices of a spatial graph used for the calculation (Figure 3). The point distance was set to 5m, representing a good trade-off between computation time and

[6] A distance decay parameter β of 0.00217 in metres correspond to 0.1813 in temporal units as defined by Handy & Niemeier (1997)

precision. Based on experimental results showing no significant deviation in the ASA index, this discretisation setting is considered a good approximation of a continual distribution.

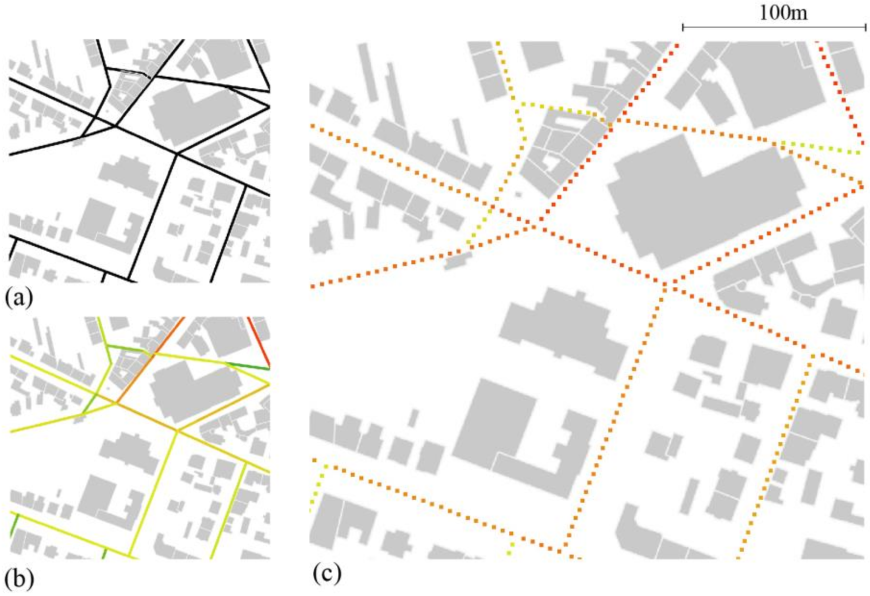

Figure 3. Discretisation of spatial network (a) Segment map (b) *Betweenness* R600 (red = high *Betweenness*, green = low *Betweenness*) (c) Discretised spatial network to evenly distributed points (5m distance)

Results – Case study Weimar

In the following section, we present an empirical study that aims to test the research hypothesis and measure the ability of the ASA method to predict the AWA based on the street network configuration. First, we test the hypothesis that the street network configuration affects the pedestrian movement flows and could be effectively used to estimate them. For this purpose, we collect empirical data on pedestrian movement and fit a linear regression model[7] in order to quantify the relationship between the configuration and movement. Second, we test the hypothesis about the influence of pedestrian movement flows on the AWA. We assume that the distribution of pedestrians correlates with distribution of walking attractors. Therefore, the accessibility of pedestrians is expected to correlate with the accessibility of walking attractors. We test the second hypothesis by measuring the relationship between the estimated accessibility of pedestrians (ASA) and the empirical measure of AWA assessed via publicly accessible

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[7] Previous studies on the relationship between pedestrian flow and street network centrality suggest a linear relationship between the variables (Hillier, et al. 1993; Penn 1997; Turner & Dalton 2005)

online service known under the term Walk Score. At the same time, the strength of the relationship between ASA and AWA will quantify the ability of the proposed model to predict the accessibility of walking attractors based on the street network configuration.

We test the hypothesis in a pilot case study conducted in the city of Weimar, Germany. For the purpose of evaluating the influence of the street network configuration on pedestrian movement, Weimar offers a rich data sample consisting of a wide range of street network patterns, from organically evolved medieval city centre, to regular grids of 19th century city expansion areas and large slab-housing estates built in the 1970s (Figure 4). Furthermore, the size of the city (64,131 inhabitants, 84,420 km^2) makes it possible to cover and analyse the city as whole, which eliminates the 'edge effect' that can bias the partial analysis of larger urban systems (Gil 2015)[8]. Its compactness also promotes walking as a main travel mode, which complies with the focus and methods chosen in the ASA. Additionally, Weimar also exhibits high variance in the AWA measured by Walk Score, ranging from 10 to 100 points, i.e. "car-dependent" to "walker's paradise".

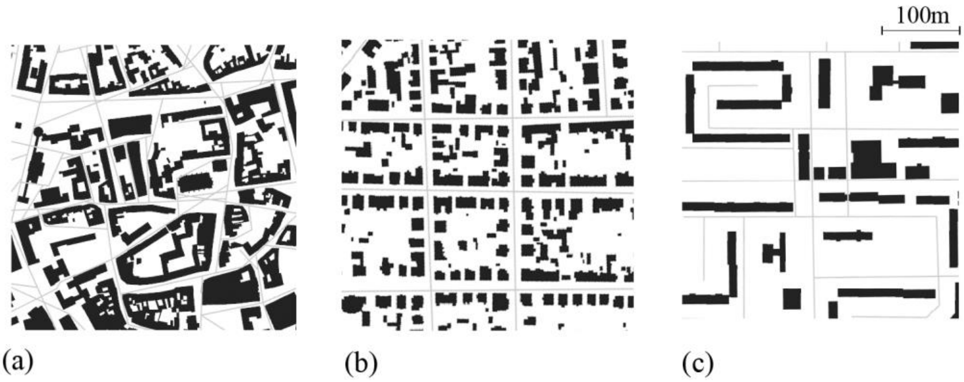

Figure 4. *S*treet network patterns and building densities found in Weimar. (a) Historical center (b) Regular grid (c) Large housing estates

The Walk Score index is a web-based service calculating the AWA and thus the walkability of an environment. It is measured by on a scale of 0 to 100 points, where the

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[8] In the analysis of spatial networks, the 'edge effect' describes a bias in the analysis results as a product of portion of the network included in the analysis – the edge (Okabe & Sugihara 2012). Different measures have different degrees of sensitivity towards the 'edge effect', mostly depending on the radius of the analysis (Gil 2015). In the case study presented in this paper, we avoid the 'edge effect' by analyzing the whole city of Weimar. Since no additional settlements were found within the boundary of the maximum analysis radius (2000m) from the edge of the city, there would be no change in analysis results if the edge were extended.

contribution of walking attractor to the overall score depends on its type[9] and network distance from the evaluated address. A distance decay function is used to award attractors within a 0.25 mile radius maximum points and ones at a distance of more than 1 mile (30-minute walk) with no points (Oishi et al. 2015). The major advantage of Walk Score is its availability, since all the data required for the calculation has been already collected and is freely accessible from third party services such as Google Maps, Education.com, Open Street Map, the US Census and Localeze (Duncan et al. 2012). This makes it possible to automatically assess the Walk Score index for any location resulting in a data sample about environmental quality which is unprecedented both in size and level of detail[10].

Data collection

In order to test the street network configuration as a predictor of pedestrian movement, we conducted an empirical study counting the pedestrian flow. From 14-20 March 2016, we collected data from 120 locations spread all over the city covering low to highly frequented locations. For each location, we repeated the exercise on three different days (one weekend and two working days) and three times each day (8-10am, 12-2pm, 4-6pm). Consequently, we gained nine measurements for each location, which make it possible to eliminate outliers and temporal fluctuations in pedestrian flow. To examine how the distribution of movement varies among the nine measurements, we calculated the Pearson correlation matrix for all their combinations = 36 correlations (Table 1). The average Pearson correlation coefficient of 0.802 suggests that the movement flow remains relatively stable. As a result, we calculated the mean of the nine measurements for all 120 locations as the best representative of pedestrian movement.

[9] Walk Score recognises eight types of walking attractors: Errands, Culture, Grocery, Park, Dining and Drinking, School, Shopping (walkscore.com). Their individual weighting was empirically calibrated based on their contribution to moderate and vigorous physical activity (Frank 2013).

[10] The resolution of Walk Score is on the level of the individual house. Walk Score can be assessed for any location worldwide, however location outside the US, Canada, Australia and New Zealand should be additionally validated, since the geo-located data is not always complete (walkscore.com).

Table 1. Pearson's correlation matrix showing the correlation coefficient R for nine pedestrian-counting sessions. Significant correlations are marked with * (p value ≤ .05).

	Weekend 8-10am	Weekend 12-2pm	Weekend 4-6pm	WD. 8-10am	WD. 12-2pm	WD. 4-6pm	WD2. 8-10am	WD2. 12-2pm
Weekend 12-2pm	0.728*							
Weekend 4-6pm	0.674*	0.956*						
Working Day 8-10am	0.689*	0.845*	0.88*					
Working Day 12-2pm	0.646*	0.873*	0.908*	0.864*				
Working Day 4-6pm	0.688*	0.887*	0.922*	0.903*	0.928*			
Working Day2 8-10am	0.659*	0.714*	0.726*	0.774*	0.67*	0.757*		
Working Day2 12-2pm	0.675*	0.839*	0.892*	0.85*	0.959*	0.911*	0.692*	
Working Day2 4-6pm	0.602*	0.746*	0.866*	0.835*	0.868*	0.861*	0.688*	0.911*

Note: WD: Working Day, WD2: Working Day2

The digital model of the movement network consisting of axial lines split at their intersections was manually drawn for the whole city of Weimar following the Space Syntax method described in previous section. The resulting model of 3272 line segments (referred to here as the street network or spatial network) was geo-localized in order to assess the respective *Betweenness* centrality, the ASA and Walk Score. All calculations described in the method section necessary to assess the ASA based on the data on street network were carried out in the DecodingSpaces spatial analysis toolbox for Grasshopper, Rhino[11]. The Walk Score data was automatically assessed via a web API offered by walkscore.com. The API received the latitude and longitude of the midpoint of all 3272 line segments from the Weimar street network and returned the calculated WS. A subset of the WS data received via API (120 observations) was validated against manually assessing the WS using the standard web interface. We can summarise that no differences were detected. All statistical evaluations were conducted using the R statistical programming language[12].

[11] Whitepaper describing the functionality of the DecodingSpaces toolbox is available at: https://e-pub.uni-weimar.de/opus4/frontdoor/index/index/docId/2738

[12] R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.

Street network configuration as predictor of pedestrian movement flows

To quantify the relationship between *Betweenness* centrality as measure of movement potential and counted pedestrian movement, we assess the R-square as a measure of fit calculated in the linear regression model. To comply with the normal distribution criteria of linear regression, we logarithmically (LN) transform both variables to correct the original right skewed distribution. It should be noted that other models, such as Poisson regression, might be a better choice for predicting a time-sequence variable such as movement flow and would not require the transformation of the data. However, since our goal is measurement of the relationship, we argue that these models are less suitable for our purposes since they do not offer any equivalent to R-square.

Additionally, due to the high sensitivity of *Betweenness* centrality results to the choice of analysis radius, we systematically investigated the relationship between radius definition (from 100 to 2000m) and the ability of *Betweenness* centrality to predict pedestrian movement (Figure 5). The highest $R^2 = 0.491$ (p value ≤ 0.001) was found for a radius of 600m (or a seven-minute walk). Furthermore, we observe that the radius is more sensitive in a lower distance range, peaking at 600m and then slowly falling towards a distance of 2km with $R^2 = 0.058$ (p value ≤ 0.05).

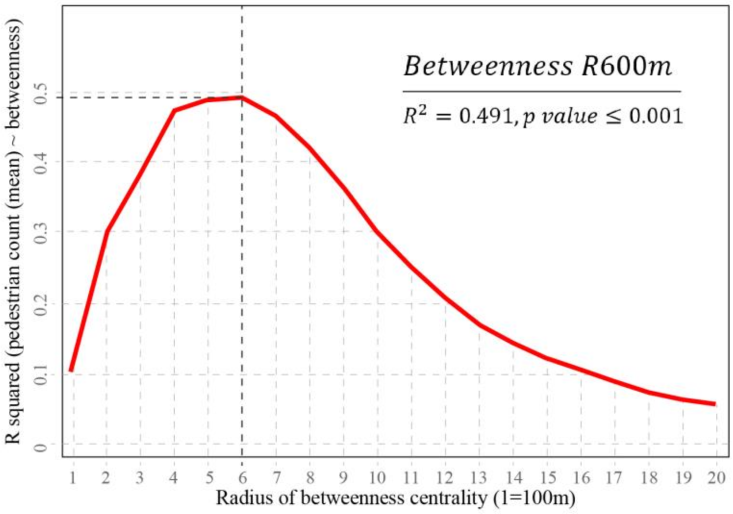

Figure 5. Graph showing the relationship between the radius of *Betweenness* centrality (in 100m steps) and its ability to predict pedestrian movement (in R^2)

By examining the residuals, we were able to identify several causes of deviation between movement potential and actual measured movement. These were mainly traced to the allocation of special functions and to buildings of historical or cultural importance which amplified movement but did not add movement potential to the network (i.e. touristic sights, such as the birthplace, residence and monuments of Goethe and Schiller; the train station, etc.) (Figure 6). Despite these deviations, we can nevertheless conclude that the calculated street network movement potential (*Betweenness* R600) in the case of Weimar provides a significant and strong estimate of the measured pedestrian movement.

Figure 6. Residuals of linear regression model with *Betweenness* R600m as an independent variable and measure of pedestrian flow as the dependent variable for all 120 observations. The size of the circle is proportional to the value of residual (highest residual = biggest circle diameter) and its colour identify the direction of the deviation (Red = positive residuals, Blue = negative residuals)

Pedestrian movement flow as a predictor of the access to walking attractors

Once the inner consistency of the ASA method was successfully tested (first hypothesis), we evaluated the second research hypothesis stating that the access to walking attractors and access to people are strongly related. The access to people is calculated by discretising the continuous movement flows into single points (see method section) and evaluating the contribution of each point to the overall accessibility. This contribution is proportional to the intensity of movement flow at a given location and inversely proportional to its network distance. The ASA index is calculated for the midpoint of every street segment in Weimar (3272 segments) as a common spatial unit for all graph-based calculations in the presented method (Figure 7).

Figure 7. ASA outcome mapped onto the street network (Red = High ASA, Blue = Low ASA).

The hypothesis is evaluated by measuring the measure of fit between calculated ASA as a predictor and AWA empirically measured by Walk Score index as the outcome variable in a linear regression model. Special attention must be paid to the conceptual difference of the allowed range adopted by ASA and Walk Score, which has consequences for the order of the regression model and shape of the fitting curve[13]. The ASA is defined as a range from 0 to infinity whereas Walk Score starts at 0 but has a cut-off value of 100. As consequence, we observe a curvilinear relationship with accelerating radius as Walk Score approaches the 100-point cut-off and ASA continues to rise (Figure 8). The ASA, as a measure of access to people, was a significant predictor of the Walk Score (β_1 = 6.881e-03, β_2 = 7.542e-08, β_3 = -9.624e-12), accounting for 84.12% of the variance ($R^2 = 0.841$, $p \leq 0.001$). Based on this strong, significant relationship, and the model evaluation in terms of the residual analysis (see Appendix 1) we conclude that the case study of Weimar confirms the validity of our hypothesis.

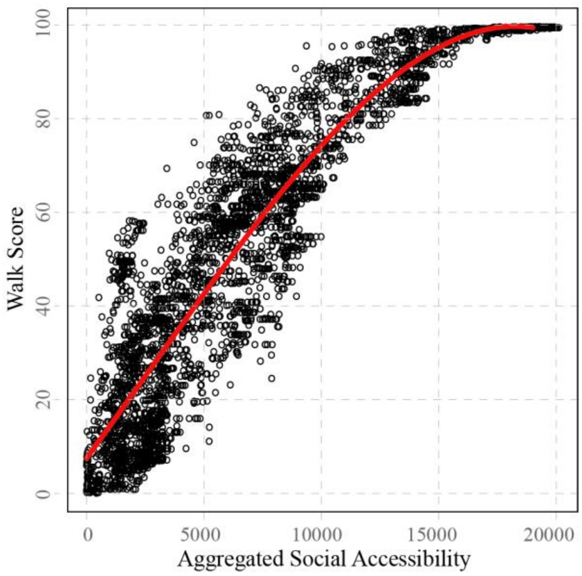

Figure 8. A scatter plot showing the relationship between ASA as a predictor and Walk Score as the outcome variable with fitted regression line.

Discussion

The hypothesis testing confirmed the significant effect of street network configuration on pedestrian movement as suggested by previous studies. In the case of Weimar, the angular *Betweenness* centrality accounts for 49% of variance in the empirically-measured pedestrian flow with the maximum prediction power achieved at a radius of 600 m. Furthermore, we observed that variations of building density or allocation of special functions that don't follow the movement potential of the street network might be

[13] We modeled the curvilinear relationship between ASA and AWA by fitting the polynomial regression function. The best fit maintaining all regression parameters significant was achieved by 3rd degree polynomial function.

responsible for distortions in the relationship between estimated and measured movement. In our case, these effects were present, but played a minor role as already confirmed by previous studies (Bielik et al. 2015). However, in general, these limitations might restrict the applicability of the presented method. As a consequence, we see a clear need for further examination of the relationship between building density, allocation of movement attractors and network centrality in order to (a) identify cases where *Betweenness* centrality has limited ability to predict movement, and (b) to extend the current model in order to deal with these cases. Despite these limitations, we argue that the angular *Betweenness* centrality is especially helpful in the planning process. Even though the assumptions of the model might not always match reality, it can still can be applied as a neutral benchmark in order to deliberately foster or weaken the movement potential of a street network by varying building density and land use allocation. Based on the empirical results and our objective of using the ASA method in the planning process, we consider the angular *Betweenness* centrality a good estimate of pedestrian movement flows.

Regarding the second hypothesis, we found that ASA measuring the access to pedestrian movement flows based on street network configuration is a significant predictor of AWA. In our case study, the ASA alone accounts for 84% of variance in AWA measured by the Walk Score index. This result offers strong support for the research hypothesis, stating that access to people is related to access to walking attractors. The remaining 16% of variance in Walk Score which were not captured by the ASA might be attributed to (a) the limited ability of the method to estimate pedestrian movement as discussed earlier, and (b) the definition and weighting of the Walk Score function since it was calibrated for a North American context. With regard to the first point, we argue that a better predictor of pedestrian flow would improve the overall performance of ASA, but that even a coarse pedestrian flow estimate can produce a relatively precise measure of access to pedestrian flows. This seemingly counter-intuitive observation is mainly a product of the smoothing effect of the adopted gravity function, which reduces the impact of local deviations in estimated pedestrian flow (see Appendix 2). We assume that this holds true if deviations in movement flow prediction are randomly distributed throughout the spatial network, although this has to be further investigated in future studies. Regarding the second point – the Walk Score methodology – the empirical data clearly shows that the Walk Score threshold value for the maximum score might be too low for denser, historically-evolved European cities. Additionally, the 1.6 km radius adopted by Walk Score may not reflect the maximum walking distance for different cities as suggested in previous research and confirmed in this study (in Weimar a radius of 600 m was found to be the best predictor of pedestrian flow).

Nevertheless, if our results are confirmed by future studies, the consequences will be much more substantial than the ability to predict AWA during the planning process. Since

ASA doesn't consider any other information aside from the street network, the preliminary results suggest that its configuration alone is the most influential variable for defining access to people and walking attractors. Furthermore, the strong relationship between ASA and AWA shows that access to people is an important predictor of environmental quality.

Conclusions

The main goal of this study was to inform the planning process by predicting the influence of street network configuration on the walkability of an environment based on access to walking attractors. To this end, we developed and empirically tested a predictive method we have called Aggregated Social Accessibility (ASA).

We found that the configuration of a street network is a significant predictor of the pedestrian movement flows. Furthermore, we confirmed the research hypothesis by identifying evidence for a relationship between access to pedestrian movement flows and access to walking attractors. The ASA method presented here was found to be a strong predictor of Walk Score – an established measure of AWA. As a consequence, we present empirical evidence showing that the spatial network, access to people and the walkability of environment are closely related.

In order to generalise current results and determine causality in the presented findings, further case studies are necessary and currently in preparation.

Acknowledgements

This study was carried out as part of the research project ESUM - Analysing trade-offs between the energy and social performance of urban morphologies funded by the German Research Foundation (DFG) and Swiss National Science Foundation (SNSF).

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Appendix 1

ASA *as Predictor of AWA (Walk Score) – Residual Analysis*

To validate the predictive linear regression model of Walk Score based on the ASA we conduct the regression residual analysis. First we examine the residual variance (Figure 9a). We found uniform distribution of residual variance with decrease at maximum Walk Score values. This could be accounted for the fact that Walk Score index as opposed to the ASA has introduced artificial cut-off value at 100 points. As next we test the normality of error terms (Figure 9b) and observe that the residuals follow the normal distribution. Finally, the leverage plot (Figure 9c) doesn't indicate any potential measurement errors and their influence on the regression model. We conclude that the residual analysis didn't reveal any systematic patterns indicating errors in the predictive model.

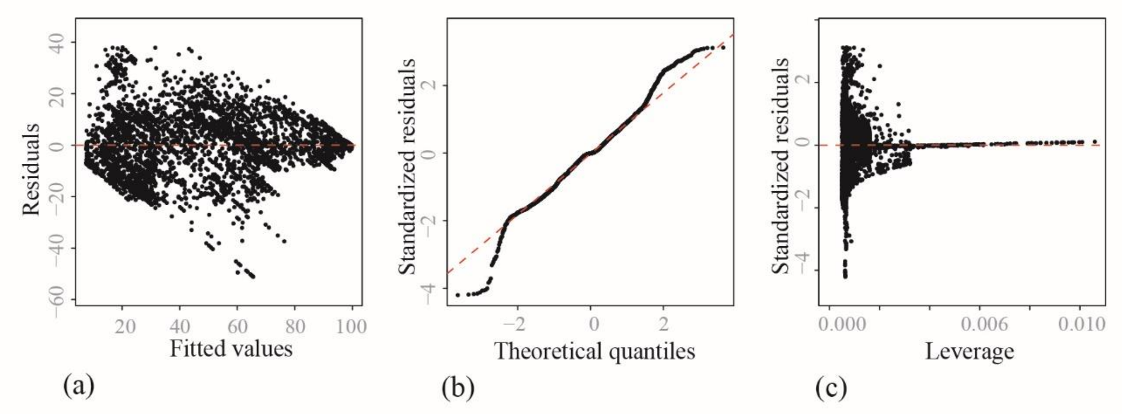
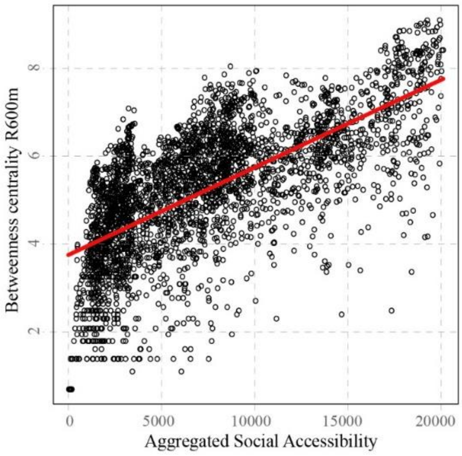


Figure 9. Residual plots: (a) Residuals vs. Fitted values, (b) QQ plot and (c) Residuals vs. Leverage

Appendix 2

Pedestrian Movement Flows vs. Access to Pedestrian Movement Flows

The relation between predicted movement flows and the access to these movement flows show the high collinearity of both measures (Pearson's correlation coefficient R = .67, p value ≤ .001, see figure 10b). However, we observe discrepancy at locations with a rapid drop of movement between neighboring street segments. While this high deviation in movement flows among geographically close locations is a common phenomenon in street networks, physical access to an opportunity doesn't change abruptly every few steps (Figure 10a). With this in mind, we can consider the ASA as smoothing function of movement potential.



(a) (b)

Figure 10. (a) Movement potential (*Betweenness* centrality R600m) mapped onto the street network (Black = High *Betweenness*, Light grey = Low *Betweenness*) and access to movement potential (ASA) mapped onto buildings (Red = High ASA, Blue = Low ASA). (b) A scatter plot showing the relationship between ASA and b*etweenness* centrality R600m