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What Does Walk Score® Really Measure?

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What Does Walk Score® Really Measure?

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1. Introduction

In recent years there has been an increase in the interest, research and study of the concepts of accessibility, land use, travel behavior and walkability. These topics have become very important to planners, engineers and policymakers across the world as they work together to make decisions in the development and redevelopment of urban places and their related transportation infrastructure. These groups are increasingly embracing the mandate to use smart growth and sustainability strategies when spending the public sector's limited resources. Additional empirical studies are needed to help provide examples and guidance to develop a framework on which decision makers can act.

The motivation behind this thesis came from two studies done in 2010 and 2011 on the effects of street network design on walking and biking (Marshall and Garrick, 2010), traffic safety (Marshall and Garrick, 2011), and health outcomes (Marshall, Piatkowski and Garrick, 2014). These studies found that street network measures such as Node Density, Link-to-Node Ratio, and Network Typology were significantly correlated with mode choice, traffic accident severity and health outcomes for people living in 24 medium sized California cities. The results showed that more connected street networks with higher intersection density had higher percentages of people walking and biking as well as lower levels of severe traffic accidents. However, the two studies from 2010 and 2011 were developed based on data for characterizing the built environment that required time consuming and costly collection efforts. Therefore, identifying more readily available measures of access, street design and network characteristics would help to facilitate this line of research.

Technological advances over the last decade have resulted in algorithms and processes for synthesizing large amounts of data with much less effort than in the past. Geo-spatial mapping and attribute coding tools have been at the forefront of this movement providing valuable opportunities for research into transportation infrastructure, land use, walkability and accessibility. However, the greatest benefit of these technological advances has been the public's ability to obtain and use this data.

In 2007, the technology incubator Front Seat began development of the Walk Score® (WS), a metric created to help people evaluate the walkability of specific locations. With a simple street address search, you get a map with nearby amenities and a walkability score. The Walk Score® (WS) algorithm works by identifying the closest amenities (for example, grocery stores, banks, restaurants, and schools) and awarding points based on the distance to amenities from a given location. Location scores have a range between 0 and 100, with 100 being the best.

In 2011, the Walk Score® (WS) founders and advisory board modified the algorithm to better account for pedestrian friendliness by adding block length and intersection density data into the model to represent roadway characteristics (walkscore.com). Although this version was originally named Street Smart Walk Score® (SSWS), the name never made it to into the public sphere. However, the algorithm was accepted and incorporated into what is now used for scores on the Walk Score® web service.

Modelers attempting to quantify accessibility often focus on two components: a transportation element (or resistance factor) and an activity element (or attraction factor) (Handy 1993). The transportation element often considers variables such as infrastructure, topography, route directness, as well as distance, travel time, or cost. Activity factors are measured from objective variables such as destination locations, parking availability, land-use density, land-use mix, and subjective variables such as the perceived quality of products at destinations. It is generally believed that Walk Score® (WS) and Street Smart Walk Score® (SSWS) account for both the land use and the street network elements of accessibility measures. However, the extent to which these metrics accurately represent these variables has not been fully evaluated by research. The goal of this thesis is to determine if Walk Score® (WS) and Street Smart Walk Score® (SSWS) are true measures of accessibility in fully representing both transportation and activity.

In this body of work, Walk Score® (WS) and Street Smart Walk Score® (SSWS) are analyzed to understand if they adequately account for street network density, street network connectivity and street design characteristics – all of which are key aspects of the transportation element of accessibility. To achieve this, the following steps are taken. First, Walk Score® (WS) and Street Smart Walk Score® (SSWS) are compared using a dataset of over 1000 block groups in 24 medium-sized California cities. Then, Street Smart Walk Score® (SSWS) is compared to street network measures and street design characteristics. Finally, a sensitivity analysis is used to assess the effects on mode choice by features such as Street Smart Walk Score® (SSWS), street network measures, street design characteristics, and land use measures. The study concludes with a discussion of the findings and recommendations relating to the use of Walk Score® (WS) and Street Smart Walk Score® (SSWS).

2. Literature Review

The literature used to support this study highlights the following three points: (i) The definition of accessibility which creates the framework for understanding how to assess if Walk Score® (WS) and Street Smart Walk Score® (SSWS) are truly representative of both transportation and activity, (ii) Walk Score® (WS) validation studies whose findings are in agreement with the hypothesis that the Walk Score® (WS) does not account for the transportation element, rather it is a good measure of access to destinations, and (iii) Literature from the Walk

Score® web-service to understand the current algorithm and components of Street Smart Walk Score® (SSWS).

The transportation element of accessibility is generally characterized by the built environment – and due to advances in computing power, data management methods, and Geographical Information Systems (GIS) – attempts to measure this element have expanded greatly over the years. Combined with an abundance of free secondary data, researchers have not only amassed large datasets but have developed long lists of variables representing the characteristics of the built environment that have proved significantly associated with phenomena such as travel behavior, road safety, physical activity, and public health (Cervero & Gorham 1995; Portland Metro 2004; Handy & Mokhtarian 2005; Bartholomew & Ewing 2009). Now accessibility modelers are more equipped than ever to assess core features of the built environment.

Similarly, these advances in technology and data collection techniques have vastly influenced the composition of the activity element of accessibility. Research has grown in the application of GIS tools and methods of spatial analysis to find physical accessibility to amenities or valued destinations (Black et al. 2004; Ortega et al. 2005; Zhu and Liu 2004). This growing body of research has opened the door for amenity driven studies, such as is the case of the topic of walkability. Using GIS to create large datasets of origins and destinations, researchers are now able to look at the relative attraction of amenities to determine their importance on outcomes such as walkability, health, and travel behavior among others (Cerin et al. 2007; Rattan et al. 2012).

More recent developments of web-deployed GIS systems have pushed tools – with the ability to create, manage, and analyze large datasets quickly and efficiently – into the hands of the public. This has prompted research and development of new metrics, such as the Walk Score® (WS), which are reshaping the characterization of the attractiveness/activity element of accessibility by providing an almost universal data set of measures that were previously difficult to obtain.

The Walk Score® (WS) algorithm works by identifying the closest amenities (for example, grocery stores, banks, restaurants, and schools) and awarding points based on the distance to amenities from a given location. Scores range between 0 and 100. Amenities within a quarter-mile walk are awarded the maximum points and “a distance decay function is used to give points to more distant amenities, with no points given after a 30-minute walk” (walkscore.com). According to the method outlined by walk score, a 30-minute walk is approximately a distance of 1.5 miles ‘as the crow-flies’ (walkscore.com). A problem that WS does not address is that using a 1.5-mile radius does not account for the fact that the built environment can vary greatly within those limits. Aspects such as intersection density, street network connectivity, street widths, presence of sidewalks etc. are important infrastructure features that play a major role in whether people feel safe enough to walk. More importantly, the actual walking distance within a 1.5-mile radius can be much greater than the ‘as the crow-flies’ distance depending on the street network.

In part due to the proliferation of measures such as the Walk Score® (WS), research based on walkability indices has grown rapidly over the last few years. Multiple studies have shown Walk Score to be a valid measure of accessibility to amenities and highly correlated with real estate prices, physical activity, health and travel behavior (Rauterkus et al 2010; Armstrong and Greene 2009; Pivo and Fisher 2010; Jones 2010; El-Geneidy and Manaugh 2011). More specifically, a study comparing four walkability indices - WS, Walk Opportunities, Walkability Index (WI), and Pedshed Connectivity - concluded “…the examined indices are highly correlated with walking trips for most non-work trip purposes” (El-Geneidy and Manaugh 2011). Out of the four walkability indices, “the Walk Score® explained as much, if not more, of the variation in walking trips to shopping". However, it was not the best index for explaining trips to school. This could be due to the inherent calculation methodology behind the Walk Score® (WS), which gives more weight to shopping type amenities over schools and parks. In fact, groceries and shopping are given two to three times more weight than schools (walkscore.com 2010).

Additional studies focusing on validation of the Walk Score® (WS) metric have come to the consensus that "…Walk Score is a valid measure of estimating neighborhood walkability in multiple geographic locations and at multiple spatial scales" (Duncan et. al 2011). More importantly, "...Walk Score is a reliable and valid measure of estimating access to walkable amenities" (Carr et. al 2010). This study found that in addition to Walk Score® (WS) already being valid as an accessibility estimation tool, there was a strong and positive correlation between street network characteristics and Walk Score® (WS).

In a study of 296 origins/ addresses in the state of Rhode Island, intersection density and street density were observed to have Pearson correlation statistics of 0.81 and 0.74 with Walk Score® (WS), respectively. The study by Carr in 2010 had a very small sample size for which the mean intersection density was 651 with standard deviation of 369, and the mean population in 1 mile was 18,681 with standard deviation of 13,569. However, in a follow up study in 2011 using a sample of 733 address in metropolitan areas across four geographic regions in the U.S., Carr found correlations of 0.65 between WS and intersection density. Yet, Carr still concluded that WS is a valid measure of walkability because it is "more predictive of walking behaviors than single walkability metrics and because Walk Score is free, quick and easy to use" (Carr et. al 2011). This claim will be further investigated in our study by using a larger sample size. The data used for this study is a collection of street network variables, street design features, land use variables, and demographic and mode choice variables for over 1,000 Census Block Groups.

Further development of the Walk Score® (WS) took place in 2011 based on additional research by the metric's founders and advisory board. That year, the algorithm was modified to better account for pedestrian friendliness by adding data into the model to represent roadway characteristics (walkscore.com). Although this version was originally named Street Smart Walk Score® (SSWS), the name never made it to into the public sphere. The algorithm however, was accepted and incorporated into what is now used for scores on the Walk Score® web service.

The Street Smart Walk Score® (SSWS) metric is formulated in a very similar way to the original Walk Score® (WS). Both use a distance decay function for the same nine amenity types with the same weights to produce a score from 0 to 100. However, the Street Smart Walk Score® (SSWS) uses an added step to assign a penalty to each location based on what is referred to as "…poor pedestrian friendliness" (Walk Score® 2011). The Walk Score literature states that the pedestrian friendliness metrics considered by the new algorithm are intersection density and average block length. The new formulation can impose a penalty of up to 10% of the total score depending on the quality of these pedestrian facilities, up to 5% for each. (Walk Score® 2011).

An issue with Street Smart Walk Score® (SSWS) is that block length and intersection density are virtually the same. As block lengths increase, the density of the intersections will decrease and vice versa. The SSWS however, does not consider factors such as street connectivity or street design characteristics which are commonly associated with more pedestrian and bicycle friendly places. Yet, by the simple addition of the block length and intersection density, the SSWS still does not address questions such as: how far is the actual walk? Is it safe to walk on this street? Are there sidewalks? or Is it a comfortable walk? Therefore, scores given to locations are mostly representative of the available amenities and less a representation of the infrastructure around them. In this study, we will attempt to address the extent to which this is a problem.

3. Methodology

To understand if Walk Score® (WS) and Street Smart Walk Score® (SSWS) truly account for key aspects of the transportation element of accessibility the following methodology was employed. Walk Score® (WS) and Street Smart Walk Score® (SSWS) were compared against each other using a dataset of over 1000 block groups in 24 medium-sized California cities. Next, relationships between Street Smart Walk Score® (SSWS), street network measures, street design characteristics and land use measures were analyzed using a correlation analysis. Then, a sensitivity analysis was used to assess the impacts of the SSWS, street network variables and street design characteristic on mode choice. A discussion of the results and recommendations relating to the use of Walk Score® (WS) and Street Smart Walk Score® (SSWS) concludes the study.

3.1. Data

Most of the data for this thesis came from two studies done in 2010 and 2011 on the effects of street network design on walking and biking (Marshall and Garrick, 2010), and safety (Marshall and Garrick, 2011), respectively. For this thesis we focused on the 2010 study which analyzed the effects of street network measures on travel behavior. That 2010 study found that street network measures such as Node Density, Link-to-Node Ratio, and Network Typology were significantly correlated with mode choice for people living in 24 medium sized California cities. The data used for that study is a collection of street network variables, street design features, land use variables, and demographic and mode choice variables for over 1,000 Census Block Groups.

The street network variables were compiled using the ArcGIS tools Spatial Analyst and Network Analyst. Spatial and street centerline data was collected from a variety of sources including the U.S. Census TIGER lines files, the California Department of Transportation

(Caltrans), and the California Spatial Information Library records. The variables calculated using this data include intersection density, link-to-node ratio, and a categorical variable for network configuration. To adequately represent the street network configuration Stephen Marshall's macroscopic and microscopic network descriptions, which can be seen in **Figure 1**, were adapted to create a street configuration classification system based upon citywide and neighborhood street types (Marshall 2005).

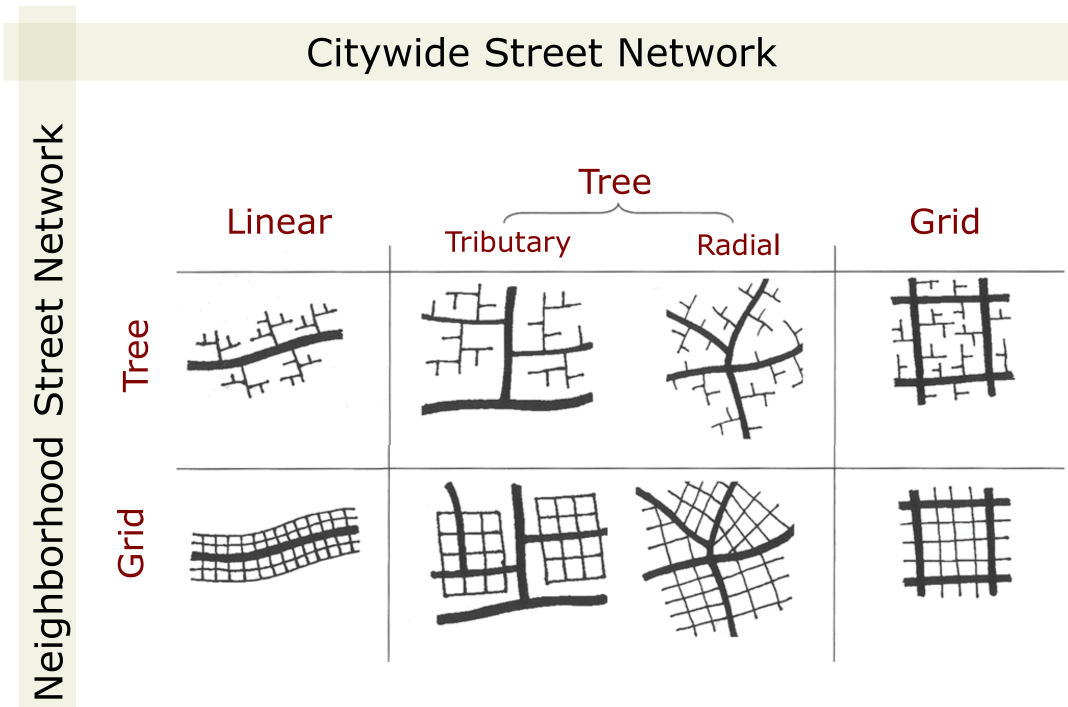


Figure 1. Network Classification System (Marshall 2005)

To overcome the potential drawback of omitting curvilinear streets from the classification scheme, a binary variable was added to represent whether the network was generally curvilinear. To do this, ArcGIS was used to analyze and highlight the citywide and neighborhood street types. Then each of the more than 1,000 Block Groups was assigned the most predominant pattern type at both the citywide and neighborhood levels (Marshall and Garrick 2010).

The street design variables were compiled from a combination of sources including Google Earth Aerial Photography, and Google Street View images. Street design characteristics were collected for all citywide street segments in each city. The data was compiled and analyzed using a combination of ArcGIS and Access database management tools. The data collected included the following:

- Average Total Number of Lanes
- Average Outside Shoulder Width
- Raised Median Width
- Painted Median Width
- On-Street Parking (0 =no, 1 = yes, 0.5 = along one side)
- Bike Lanes (0 =no, 1 = yes, 0.5 = along one side)
- Curbs (0 =no, 1 = yes, 0.5 = along one side)

Two proxy variables to account for the activity and the land use distribution of each Block Group were included. The two variables were calculated using a simplified gravity model approach originally conceived by Graham and Glaister in 2003.

For the activity variable, the strategy used by Marshall and Garrick was to establish the relative activity of a Block Group in terms of the population and employment of that Block Group as well as the population and employment of other Block Groups around them (Marshall and Garrick 2010). The following equations were used to represent the amount of activity in each Block Group and originally developed by Graham and Glaister (Graham and Glaister 2003):

$$PP_i = \sum_j P_j / d_{ij} \qquad\qquad PE_i = \sum_j E_j / d_{ij}$$

For the above equations, PP_j represents the trips generated by Block Group i by the proximate population and PE_i represents the trips generated by Block Group i by the proximate employment. P_j represents the level of population, E_j is the level of employment and d_{ij} is the centroid to centroid distance between Block Groups (Marshall and Garrick 2010).

Marshall and Garrick then developed a proxy variable to account for land use within each Block Group. That was done using the proximate employment and proximate population variables. Dividing the proximate employment, E_j, by the proximate population, P_j, helped the researchers identify the relative mix of employment and population at the Block Group level of geography (Marshall and Garrick 2010). Therefore, the relative level of mixed land uses could be obtained from the following formula:

$$M_i = PE_i/PP_i$$

Additional data collected and analyzed pertain to demographics and mode choice variables. Average household income levels, mode shares, travel time to work, and other demographic data were compiled from Census data from the year 2000. The mode choice data used is made up of journey-to-work trip data within each Census Block Group. A summary of all the variables collected is shown on Table 1.

Table 1. Summary Statistics of Variables

Variable	Mean	SD	Min	Max
Street Network Measures:				
Intersection Density (intersections/sq.mi)	175.73	100.49	1.49	664.45
Dead-End Density (dead-ends/sq.mi)	32.16	28.52	0.00	248.14
Citywide Street Intersection Density (intersections/sq.mi)	60.15	70.91	0.00	664.45
Link to Node Ratio (no. of links/no. of intersections)	1.23	0.17	0.00	1.73
Curvilinear (0,1) *	-	-	-	-
Street Design Characteristics:				
Average Total Number of Lanes	2.98	1.11	0.00	7.34
Average Outside Shoulder Width	1.69	2.57	0.00	12.00
% of Citywide Street Length with Raised Median	0.52	0.50	0.00	1.00
% of Citywide Street Length with Painted Median	0.45	0.50	0.00	1.00
% of Citywide Street Length with On-Street Parking	0.50	0.40	0.00	1.00
% of Citywide Street Length with Bike Lanes	0.27	0.35	0.00	1.00
% of Citywide Street Length with Curbs	0.83	0.31	0.00	1.00
Distance from City Center (mi.)	1.84	1.40	0.03	8.98
Bisecting or Adjacent Limited-Access Highway (0,1) *	-	-	-	-
Land Use Variables:				
Walk Score® (WS)	55.36	22.19	0.40	97.20
Street Smart Walk Score® (SSWS)	47.08	26.33	0.00	98.30
Proxy for Activity	0.34	0.26	0.00	1.00
Proxy for Mixed Use	0.45	0.05	0.31	0.53
Miscellaneous Variables:				
Median Household Income ($)	57,268	21,549	11,956	128,223
Median Household Income (stand. from 0 to 1)	0.39	0.19	0.00	1.00
Vehicle-Miles-Travelled (stand. from 0 to 1)	0.06	0.07	0.001	1.00

* Binary variables included on table for information only

Overall, the data collection efforts for the 2010 study took years to complete and countless hours of effort from undergraduate and graduate students. The researchers also noted that the proxy variables were created because parcel-level land use GIS data was not available for all 24 cities. At the time of the study, using the Census data to approximate activity and land use was identified as the option requiring the least amount of effort and resources. Even with optimizing the design of the experiment for data collection and reducing the time effort required as much as possible, the 2010 study was a great undertaking. Having first-hand knowledge of the effort expended by Marshall and Garrick was part of the motivation behind this thesis. As a result, it was decided to investigate the use of more readily available metrics such as the Walk Score® (WS) and Street Smart Walk Score® (SSWS) for characterizing street networks and land use, and to investigate their relationships to travel behavior.

3.2. Comparing WS and SSWS

An analysis using the 24 medium-sized California cities dataset described in Section 3.1 was done to compare and understand the differences between Walk Score® and Street Smart Walk Score® (SSWS) relating to each other and relating to transportation infrastructure variables, street network characteristics, street design features, and the land use variables. Three statistical procedures were used for the analysis (i) a difference of means analysis using a t-test, (ii) a Pearson correlation analysis, and (iii) a regression analysis was used to compare the relationship of each metric to one another and to intersection density, link to node ratio, activity and mixed use.

4. Results

To assess the relationships between Walk Score® (WS), Street Smart Walk Score® (SSWS), and the more typical street network measures, street design characteristics and land use measures, several experimental and statistical analyses were conducted as outlined in the methodology. This section presents the findings of the Walk Score® (WS) and Street Smart Walk Score® (SSWS) comparisons as well as the results of the correlation analysis to the street network variables and street design characteristics. The results are presented using key figures and tables.

4.1. Walk Score® (WS) and Street Smart Walk Score® (SSWS)

Using all 1,040 data points, a difference of means analysis was conducted. The t-test procedure presents descriptive statistics of the differences of paired observations. The t-statistic in this analysis was 7.75, with a P-value of <.0001. Based on these findings, we fail to reject the null hypothesis that the true difference in means of WS and SSWS is equal to zero.

Next, a Pearson correlation analysis was conducted to compare r correlation coefficients for combinations of WS, SSWS and other key variables. The results of this analysis can be seen in Table 2 below.

Table 2. Pearson Correlation Analysis for WS and SSWS

Pearson Correlation Coefficients, N = 1040		
Variable	**Walk Score**	**Street Smart Walk Score**
Walk Score	1.00000	0.9446 *p*<.0001
Street Smart Walk Score	0.9446 *p*<.0001	1.00000
Intersection Density	0.6179 *p*<.0001	0.6487 *p*<.0001
Link to Node Ratio	0.3807 *p*<.0001	0.4461 *p*<.0001
Proxy for Activity	0.3874 *p*<.0001	0.3981 *p*<.0001
Proxy for Mixed Use	0.3498 *p*<.0001	0.2691 *p*<.0001

Finally, a regression analysis was used to compare the relationship of each metric to each other and to the key variables intersection density, link to node ratio, activity and mixed use. The goodness-of-fit statistic for linear regressions, R^2 was calculated for a variety of scenarios between the mentioned variables. The most significant cases are presented. When regressed upon each other, Walk Score® and Street Smart Walk Score® (SSWS) produced an R^2 value of 0.89, thus demonstrating a high degree of linear relationship between the two metrics. In the case of each metric regressed versus intersection density and link to node ratio, Street Smart Walk Score® (SSWS) had a higher linear relationship with the two variables, even though the values of R^2 were below 0.5. An interesting finding was in the relationships between the two metrics and the two proxies for land use. Of the two, Street Smart Walk Score® (SSWS) had a higher linear relationship with the variables and it was also much more significant than Walk Score® (WS).

The results from the three statistical analyses point to a very slight statistical difference if any between Walk Score® and Street Smart Walk Score® (SSWS). The results of the t-test analysis can be attributed to the addition of the pedestrian friendliness metrics to the new Street Smart Walk Score® (SSWS) algorithm. Moreover, the correlation analysis between WS and SSWS shows that although SSWS includes intersection density and block length, it is still very similar to WS. Since SSWS is the methodology currently being used and because there isn't much difference between the two, SSWS was chosen for further study.

4.2. Analysis of SSWS, Street Network and Street Design Measures

Overall, the results suggest that Street Smart Walk Score® (SSWS) is measuring something different than the street network and street design measures previously analyzed by Marshall and Garrick in 2010 & 2011. As shown in Table 3, we found that the Street Smart Walk Score® (SSWS) is slightly correlated with street network density, and not at all correlated with street network connectivity, street design characteristics or land use variables. SSWS is slightly better at considering the infrastructure, but the correlation analysis shows us that it is still not adequate.

Very slight, though statistically significant correlations, were observed between Street Smart Walk Score® (SSWS), and both intersection density and citywide street intersection density. When measured separately for local and major roads, intersection density provides an indication of the type of intersections that make up the entire street network (Marshall and Garrick 2009). The results shown above suggest that SSWS is better at accounting for intersection density than WS, which is expected given the inclusion of the "pedestrian friendliness" metrics. As mentioned previously, the pedestrian friendliness metrics considered by SSWS are intersection density and average block length. The new formulation imposes a penalty of up to 10% of the total score depending on the quality of these pedestrian facilities, up to 5% for each. (Walk Score® 2011). However, the correlation between SSWS and intersection density is not strong enough to completely account for the intersection density variable, and there is still some variation that is not explained by the Street Smart Walk Score® (SSWS) metric.

Table 3. Correlation Results for SSWS

Pearson Correlation Coefficients, N=1040	
Variable	**Street Smart Walk Score® (SSWS)**
Intersection Density	0.6487 *p*<.0001
Citywide Street Intersection Density	0.6357 *p*<.0001
Distance from City Center	-0.5635 *p*<.0001
% of Citywide Street Length with On-Street Parking	0.5490 *p*<.0001
% of Citywide Street Length with Curbs	0.4643 *p*<.0001
Link to Node Ratio	0.4461 *p*<.0001
Proxy for Activity	0.3981 *p*<.0001
Curvilinear (0,1)	-0.3674 *p*<.0001
Proxy for Mixed Use	0.2691 *p*<.0001
Income	-0.2500 *p*<.0001
Vehicle-Miles-Travelled	-0.2098 *p*<.0001
Dead-End Density	-0.1751 *p*<.0001
% of Citywide Street Length with Painted Median	-0.0756 *p*<.0001
Bisecting or Adjacent Limited-Access Highway (0,1)	-0.0621 *p*<.0001
Average Total Number of Lanes	0.0557 *p*<.0001
Average Outside Shoulder Width	-0.0534 *p*<.0001
% of Citywide Street Length with Raised Median	0.0395 *p*<.0001
% of Citywide Street Length with Bike Lanes	-0.0126 *p*<.0001

Moreover, Street Smart Walk Score® (SSWS) does not have an explicit measure of street network connectivity which has been shown to be a significant predictor of increased walking and biking. As can be seen from Table 3, the lack of correlation between SSWS and the link-to-node ratio is another indication that SSWS is not accounting for the transportation aspects.

Another important set of results from the analysis is the lack of correlation between the Street Smart Walk Score® (SSWS) and certain street design characteristics. As can be seen from Table 3, the Street Smart Walk Score® (SSWS) is not correlated to the average total number of vehicle lanes, the percentage of citywide street length with painted medians, the percentage of citywide street length with bike lanes or the average outside shoulder width. These transportation infrastructure features play a major role in outcomes such as travel behavior and in previous research have shown to be critical for completely characterizing accessibility. The Street Smart Walk Score® (SSWS) does not take these variables into consideration and therefore it is an important missing piece of the accessibility puzzle. These findings point to the fact that the Street Smart Walk Score® (SSWS) is not truly representing the transportation infrastructure and it cannot stand alone as a complete accessibility tool.

To summarize, as both the findings and the literature suggest, Street Smart Walk Score® (SSWS) does not adequately account for transportation infrastructure by the simple addition of the pedestrian friendliness metrics. Instead, it provides a quantifiable set of the land use aspect of accessibility by ranking locations based on their attractiveness and "potential opportunities of interaction" (Hansen 1959). Street Smart Walk Score® (SSWS) was chosen for the mode choice analysis because it clearly represents something different than the street network characteristics, and at the same time does not duplicate what the street network characteristics represent. In other words, the SSWS is a complimentary piece of data that could potentially replace previously used land use variables in accessibility modeling.

5. Discussion

Based on the findings above, we chose the SSWS for further analysis. Using the data for the 1,040 Census Block groups, a sensitivity analysis was used to test the effects on actual mode shares due to discrete changes on key variables. Changes on the street network density, street network connectivity, street design features, and Street Smart Walk Score® (SSWS) were analyzed. Moreover, the sensitivity analysis was conducted across the two most common types of street network configurations, Grid-Grid (GG) and Tributary-Tree (TT).

5.1. Sensitivity Analysis

Presented in Figure 2 and Figure 3 are the distributions of Street Smart Walk Score® (SSWS) values for grid-grid (GG) and tributary-tree (TT) configurations. The dataset contains 229 block groups with GG configuration and their average SSWS is 74.8. For the TT configuration there are 342 block groups and their average SSWS is 35.8. As can be seen below, there is a clear pattern pointing to the fact that there are larger number of amenities in GG configurations as compared to TT configurations.

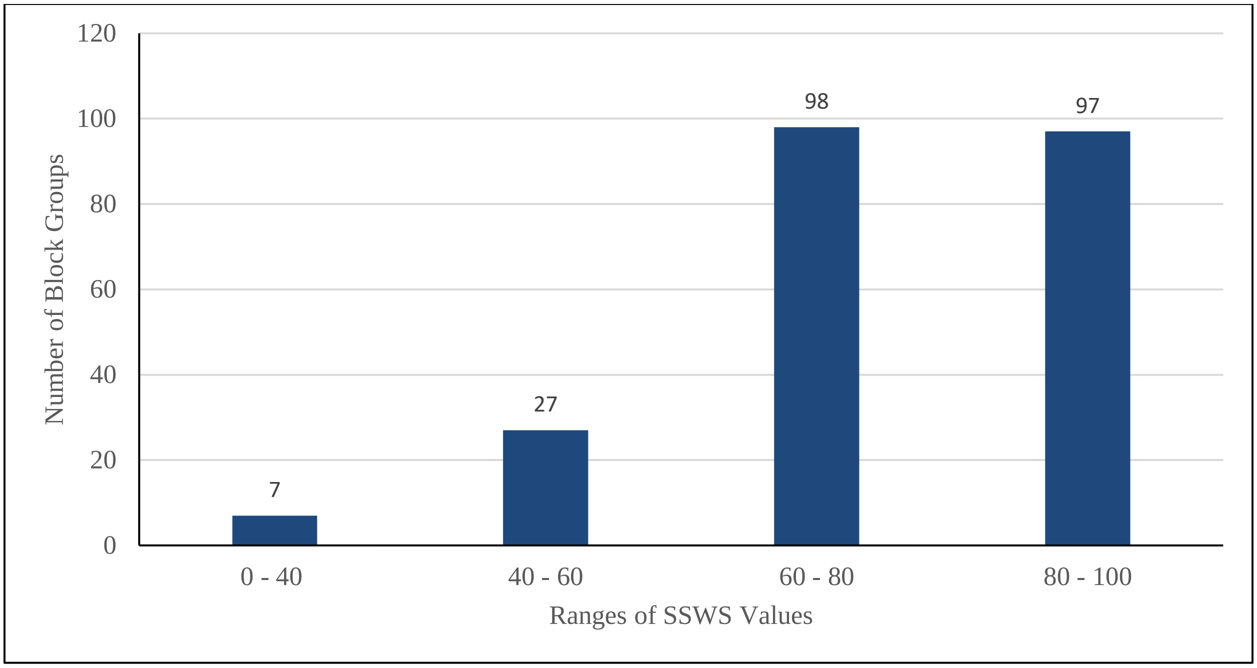


Figure 2. Distribution of SSWS Values: Grid – Grid Configuration

As show in Figure 2 and Figure 3, we split the block groups into four groups based on the range of SSWS values for each of the configurations. The groupings for the GG configuration are (i) zero to 40, (ii) 40 to 60, (iii) 60 to 80 and (iv) 80 to 100. The groupings for the TT configuration are (i) zero to 20, (ii) 20 to 40, (iii) 40 to 60 and (iv) 60 to 100. We then looked at the resulting values of street network density, street network connectivity and two important street design characteristics (average number of lanes and on-street parking) for each of the chosen SSWS ranges.

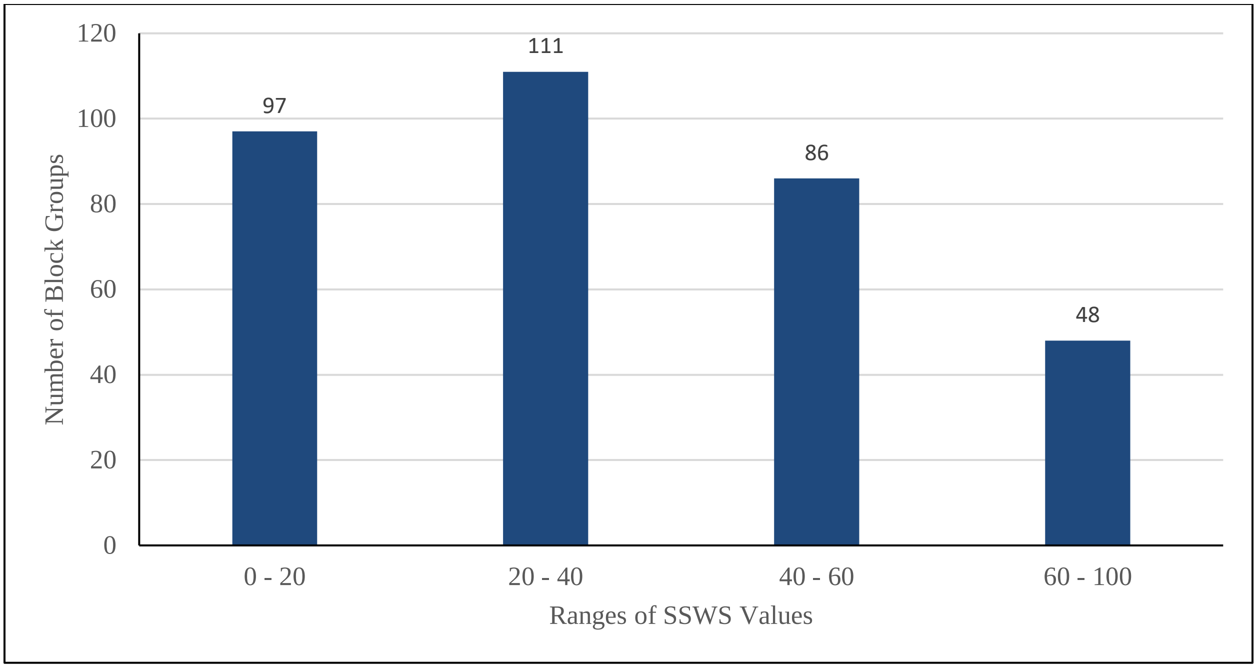
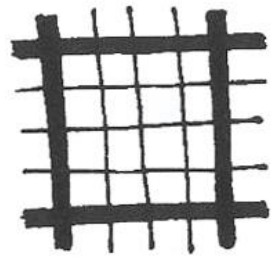


Figure 3. Distribution of SSWS Values: Tributary – Tree Configuration

Overall, increased intersection density demonstrated reduced mode shares for driving and increased non-motorized mode shares for the grid-grid (GG) configuration. As can be seen in Table 4, we found a decrease greater than 30 percentage points for driving mode shares, an increase greater than 14 percentage points for walking and an increase greater than 5 percentage points in biking when going from a lower density category (196 int./sq. mi) to a higher density category (286 int./sq.mi). These results correspond to changes in SSWS from the 0 to 40 group to the 80 to 100 group. For the tributary-tree (TT) configuration, changes in intersection density resulted in the following changes in mode shares. As can be seen in Table 5, an increase in intersection density from 97 (int./sq.mi) to 195 (int./sq.mi) corresponded with a decrease of driving mode share of approximately 10 percentage points. Meanwhile, walking and biking mode shares increased by approximately 2 percentage points and 4 percentage points, respectively.

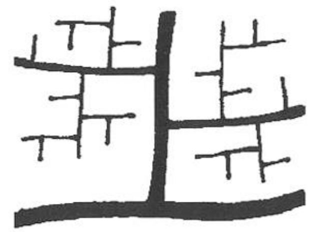
These results suggest that in terms of reducing driving, increased street network density and increased number of amenities results in a sizable difference in areas with more gridded network configurations. This supports the findings in the literature, "…related to network design variables, walking is much more strongly related to land use diversity, intersection density, and the number of destinations within walking distance" (Ewing and Cervero 2010). However, the impact of these factors is less pronounced for the TT network configuration.

Table 4. Sensitivity Analysis Results: Grid - Grid



Sensitivity Analysis: Grid - Grid									
# of Block Groups	**SSWS Range**	**Avg. Intersection Density**	**Avg. Link to Node Ratio**	**Avg. Number of Lanes**	**On-street Parking**	**Driving**	**Walking**	**Biking**	**Transit**
7	0 - 40	195.28	1.20	2.68	No	95.54%	2.57%	1.06%	0.84%
27	40 - 60	240.45	1.35	2.77	One Side	89.83%	3.16%	2.49%	4.52%
98	60 - 80	261.86	1.37	2.73	Both Sides	80.52%	5.67%	3.66%	10.16%
97	80 - 100	286.85	1.43	2.86	Both Sides	62.45%	16.52%	6.51%	14.52%

Table 5. Sensitivity Analysis Results: Tributary – Tree



Sensitivity Analysis: Tributary - Tree									
# of Block Groups	**SSWS Range**	**Avg. Intersection Density**	**Avg. Link to Node Ratio**	**Avg. Number of Lanes**	**On-street Parking**	**Driving**	**Walking**	**Biking**	**Transit**
97	0 - 20	97.01	1.12	2.55	No	93.28%	2.11%	0.78%	3.83%
111	20 - 40	132.07	1.14	2.93	No	92.67%	1.55%	2.08%	3.70%
86	40 - 60	157.16	1.12	3.28	No	87.55%	5.15%	3.28%	4.02%
48	60 - 100	195.16	1.20	3.29	One Side	82.77%	4.67%	4.45%	8.11%

Street network connectivity represented by the link-to-node ratio resulted in a lower correlation with Street Smart Walk Score® (SSWS). This correlation leads us to believe that Street Smart Walk Score® (SSWS) does not completely account for this measure in its formulation. This is not surprising since SSWS includes the average block length to assess the second penalty; however, that metric is not a measure of street network connectivity.

In the sensitivity analysis we found that increasing street connectivity, via the link-to-node ratio from 1.2 to 1.43, corresponded with an increase in walking, biking and transit use for the GG configuration. Similarly, for the TT configuration, an increase in link-to-node ratio from 1.12 to 1.2 corresponded with reduced driving and increased use of active transportation modes. More importantly, we found an overall higher percentage of driving mode share in the TT configuration as compared to the GG configuration when street connectivity as well as the amenities increased. An important finding is that at the highest levels of SSWS, the TT configuration resulted in decreased mode shares for walking.

The street design characteristics produced interesting sensitivity analysis results as well. For GG configurations, increased SSWS corresponds with practically no change in average number of lanes on the citywide streets. Therefore, the impact of average number of lanes on mode choice changes is greatly due to the level of available amenities. On the other hand, for TT configurations, we found that increases in SSWS correspond with a positive increase in average number of lanes. This is likely representative of the fact that in TT networks, typical the availability of amenities is along wider and higher speed commercial corridors. Therefore, resulting in much smaller reductions in driving mode shares when compared to GG configurations.

In terms of the presence of on-street parking on citywide streets, we found that it is more likely to find on-street parking in GG configurations rather than TT configurations. At the same time, increased SSWS values correspond more directly with the increased presence of on-street parking in GG configurations as opposed to TT configurations. For the GG configuration, going from no on-street parking to parking on both sides of the street resulted in large increases of walking, biking and transit. A key finding is that increased levels of amenities makes almost no impact on the level of on-street parking for the TT configurations. When going from SSWS values between zero and 40 to between 80 and 100, the presence of on-street parking only changed from none to on one side only. In summary, an increased presence of on-street parking on citywide streets resulted in increased walking, biking and transit, and decreased driving mode shares for both configuration types, although the effects were much greater for the GG configuration.

Generally, the Street Smart Walk Score® (SSWS) amplifies the effects that street network configuration, street network density, street network connectivity, and street design features have on travel behavior. This suggests that mode choice is greatly affected by both transportation infrastructure and destination elements. Based on the findings, we concluded that both WS and SSWS are good measures of the activity but are not representative of infrastructure aspects. A key finding is that even when amenities are equal, areas with more gridded and connected street networks with urban street features are associated with higher percentages of transit, walking and biking. Moreover, an increase in the amenities alone resulted in a much higher reduction of driving in GG configurations vs. TT configurations.

6. Conclusion

The goal of this thesis was to determine if Walk Score® (WS) and Street Smart Walk Score® (SSWS) are true measures of accessibility by fully representing destination and infrastructure aspects. It is generally believed that Walk Score® (WS) and Street Smart Walk Score® (SSWS) account for both the land use and the street network elements of accessibility measures. This was done by assessing common measures of street design, street network design, land use, and Street Smart Walk Score® (SSWS) with respect to their impact on travel behavior. Following diagnostic testing of these relationships, the Street Smart Walk Score® (SSWS) metric was determined to increase our understanding of the land use. The results suggest that the Street Smart Walk Score® (SSWS) does not completely account for the transportation infrastructure element, but rather adds to the attraction/activity element of accessibility. We found that Street Smart Walk Score® (SSWS) has a synergistic effect with street network and street design measures in mode choice outcomes and does not simply replace them.

In terms of assessing mode choice, the results from the 24 medium-sized California cities show that even though the Street Smart Walk Score® (SSWS) metric takes intersection density and average block length into account in its formulation, the metric does not fully replace street network density and street network connectivity. Moreover, the metric fails to account for street network configuration and street design characteristics, which have also been shown to be critical parts of the transportation element of accessibility.

Nonetheless, the Street Smart Walk Score® (SSWS) was found to be significant with respect to impacting mode choice. We found that people living in denser neighborhoods with high levels of amenities will drive less often and will have increased use in active transportation modes as opposed to people living in sparser neighborhoods with similar levels of amenities. More importantly, we found that the single score Street Smart Walk Score® (SSWS) cannot tell the full story. In terms of reducing driving mode shares, increased levels of amenities alone were not as significant as intersection density, street network configuration, and street design characteristics. Overall, the results suggest that higher levels of amenities in places with more gridded street networks correlated with more walking, biking and transit use.

As policy makers, planners and engineers continue to promote accessibility, it is critical that accessibility modelers can accurately and appropriately quantify characteristics of the transportation system, the built environment, and land use. This requires a more complete understanding of the role that open source measures such as the Street Smart Walk Score® (SSWS) play. The bottom line is that the Street Smart Walk Score® (SSWS) does not replace conventional street network measures; rather, the results suggest that typical street network metrics and the Street Smart Walk Score® (SSWS) have a synergistic relationship and can be used together for a better overall assessment of both the transportation and activity elements of accessibility. We conclude that the Street Smart Walk Score® (SSWS) does not fully account for the transportation infrastructure side of accessibility. Rather, it adds more to the attraction side of accessibility by directly measuring land use and amenities.

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