

SCHEMA FOR RATING MOBILITY ENVIRONMENT WITH TRAVELER PERCEPTION

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Abstract

The time-tested ways of evaluating mobility require analysis of enormous place specific data. Ostensibly, these types of cured and reliable data for settings like Nigeria are most often nonexistent or scanty, if ever they are available, not to mention the inherent limited capability of mobility models in capturing factors underlying urban mobility complexities experienced by individuals due to local factors. Consequently, it becomes necessary to seek alternative approaches of gauging urban mobility environment from traveler realities and perception, if mobility problems and their socio - economic offshoots are not to persist. To achieve this, a schema was proposed that will transform traveler perception ratings, into usable planning intervention decision support indices. The method uses data derivable from a two – staged rating survey. Stage one targets urban transport professionals, while the second is aimed at randomly selected respondents (travelers). The culminating ratings of perceived mobility enhancing and inhibitive attributes as identified by travelers are then processed using descriptive statistics, such as weighted mean and rankings to ascertain direction and degree of effect of the travel environment on travelers. Concomitantly, the calculated weighted mean and rankings are in turn used in the construction of a mobility environment assessment index for that environment. This would then allow for comparative analysis of zones within a specified setting, from which needed interventions can be gleaned. This approach will be cost-effective in identifying urban mobility challenges. The tool can also help in prioritizing interventions and identifying lagging sectors of cities. Overall, the technique provides a strategic foundation for urban mobility evaluation and practical planning where conventional methods may not be ideal.

Keywords: urban mobility, traveler perception, mobility influencers, data deficiency

Introduction

The question of inadequate or lack of data to effectively run mobility analysis conventionally for cities in the developing nations has been recognized (Aderamo, 2000). This is coupled with the lack of wherewithal and political will to gather the needed data to run such mobility analysis (Noulas, Scellato, Lambiotte, Pontil and Mascolo; 2012). This makes applicability of conventional data hungry mobility models in mobility evaluation for planning purposes in such situations farfetched (Wang, 2011). As a result, a multifaceted problem surfaces, with the most serious one being the indeterminate mobility status of such environment. Additionally, the difficulty experienced in leveraging outputs of complex mobility modeling for policy rationalization is also

a drawback in such settings, mainly due to inadequate skill and manpower (Shittu, 2014), thus, urban mobility levels in such cities remain unknown. The treatment of urban mobility issues becomes rather random, or at best subjective. City managers continually experience difficulties in identifying where, when and what kind of interventions are needed to improve urban mobility as such places evolve. Convincing the political leaders in such scenario also poses a problem. These issues have repeatedly resulted in botched attempts at improving mobility support qualities of towns and cities in Nigeria.

Another common trait in contemporary mobility models, whether employed in the evaluation of mobility patterns based on studying trajectories, dynamic proximity networks or flow on networks is that, they cannot adequately capture constraints of mobility (Isaacman, Becker, Caceres, Martonosi, Rowland, Varshavsky & Willinger; 2012; Hong, 2010). The use of time and distance parameters does not provide clues about mobility complexities facing the individual as a result of the nature of mobility environment (Calabrese, Lorenzo & Patti, 2010; Hong, 2010; Azevedo, Bezzera, Campos & Moraes, 2009), which is a critical determinant of mobility capabilities of individuals. From a more general vista, it can be added that the attributes of contemporary mobility models do not make them so much of an urban mobility planning tool, especially where required inputs to operationalized them are lacking. Several reasons underscore this situation among which are:

- i. Contemporary mobility modeling appears to further the field of mathematics, computer science, engineering and statistics more than it does transport or urban mobility planning;
- ii. They do not readily indicate required urban mobility planning solutions. Technically they have limited use in the assessment of true mobility needs of cities. Although they are useful in inferring the general distribution of a population given certain assumptions;
- iii. The explanation of population distribution based on location of urban facilities, homes and jobs, does not adequately capture the mobility support qualities of an environment. A core defining factor of mobility planning aimed at inclusivity (WBCSD; 2004);
- iv. The immediate policy usefulness of contemporary mobility modeling approaches in urban mobility planning is also debatable (Ogunsanya, 1986); and
- v. Current mobility modeling techniques are more of aids of analysis at the aggregate level (Nuolas *et al*, 2012);

Realistically, urban mobility planning tools should not just explain population distribution and assumptions on how they get to be so, but must capture how people truly overcome distance. Urban mobility planning tools should capture, in human terms, what happens at and between origins and destinations; the tools should not just explain where a subject originating from point "A" is likely to reappear, at a certain distance and time interval. The increasing complexity (Hong, 2010; Isaacman *et al*, 2012) and high technical requirements of running mobility simulations are faced with even more drawbacks in data deficient settings in that the platform is not available or lacks integrity. The temporal and economic cost of gathering the basic data for use in dedicated databases presents another challenge in data deficient situations. This is particularly so because the average data deficient city usually lacks the political wherewithal to embark on full scale, world class data acquisition programmes or projects.

As a result, it is conjectured that building and systematically evaluating perception of mobility influencing factors from the perspective of travelers may provide hints about the degree to which a city's mobility environment enhance or hinder mobility through composite indexing. Relying on the notion that perception affords the perceiver the opportunity to gather, process, and organize

information about the environment in order to make sense out of it (Kovalik and King, 1998). Perception is important because it results from sensory experience of the world around us, shaped by environmental stimuli and actions in response to these stimuli. Through the perceptual process we gain information about properties and elements of the environment that are critical to our survival (Cherry, 2014). The fact that each individual perceiver contributes in a unique manner to rating the mobility environment as either an enhancer or inhibitor of mobility is an important element of this tool. The process itself embeds democratic traits, and fosters user participation, consequently reducing the effect of top – bottom influence common in developing nations. Hence, it becomes pertinent to seek reliable options towards assessing urban mobility support qualities of cities, as a sub set of mobility analysis. Focus on indicators that can help gauge mobility ease from the context of what is deducible from the interaction between the moving subject (humans) and the containment within which mobility takes place (the environment), may offer some insight. Tapping into the culminating stated perception of travel or movement by the traveler, from which engendered inhibitors and enhancers of mobility can be deciphered may be useful in revealing pertinent interventions for urban mobility planning in data deficient settings.

Methods and Data Acquisition

In developing the template, two types of surveys are required to acquire data and information. The first one targets experts, using the Delphi method, while the second type captures the perception of the general respondents. The experts are expected to contextualize and identify factors of influence in the given environment, from the compendium of factors in the literature, after which an inter-rater consistency test using Cronbach's Alpha is applied to determine consistency of opinion of experts. The general survey then follows to elicit traveler percepts of contextually relevant mobility influencing factors, as identified by experts and to seek information regarding socioeconomic characteristics and mobility needs of respondents. As a prerequisite to technique application, experts' contextual rating of travel influencing factors is done to narrow harvested factors from literature to those that best summarize the mobility outlook of a given mobility environment. For instance, where there is no light rail system, it is taken off the list. The questionnaire or feedback form is structured in the format of a checklist. To facilitate participation, the instrument is designed to fit a 10 – 15 minutes interview. Sampling considers the official spatial sub-units of the given mobility environment, administrative or planning districts or wards as the case may be. This is important for appropriate spatial delineation, questionnaire allotment, and task planning.

Procedure for Constructing Mobility Environment Evaluation Schema

Development of the evaluation schema entails thirteen (13) sequential steps, deduced from methodology application. The flow is as listed below:

- i. Harvest of list of potential mobility influencing factors from related literature by experts;
- ii. Expert contextual relevance assessment of harvested mobility influencing factors for the given mobility environment;
- iii. Extraction of contextually relevant mobility influencing factors as per expert opinion;
- iv. Categorization of contextually relevant mobility influencing factors into thematic areas based on attribute similarities;

- v. Conducting a general mobility influencing factors' perception survey of the given zone;
- vi. Ranking of factors based on general perception survey feedback using weighted mean;
- vii. Assignment of accentuated factor Rank Order of Importance Points (ROIP) to project more important factors in a given zone;
- viii. Derivation (ROIP) factor Index Equivalents (IE);
- ix. Develop index interpretation table with mathematically attainable IE maximum and minimum accruable values;
- x. Assignment of factor Index Equivalents (IE) according to rank position;
- xi. Derivation of Average Category Index Equivalent (ACI) for thematic areas;
- xii. Computation of estimated mobility environment sub unit percept based rating of influencing factors (MER);
- xiii. Lastly, estimation of Mobility Support Level Index (MSLI) with (MER) values from sub units, then compare resultant value to the index interpretation table for description.

The ultimate aim is to identify constraints of mobility, so as to ease movement and foster adequate accessibility to component areas of a spatial entity, in a manner that will accommodate motorized and non – motorized travelers. This is expectedly achieved by enabling proper issue targeting by decision makers. The protocols of executing the above listed targets are further explained in the following sub sections.

Harvesting of Potential Mobility Influencing Factors

The target here is to derive from literature a list of factors or attributes known to affect or influence mobility of individuals, so as to create a compendium of factors from which contextually relevant ones to a particular setting can be extracted, as a precursor to presenting them to travelers for rating.

Expert Rating of Harvested Factors for Contextual Relevance

After potential mobility influencing factors are identified for the given environment. The factors are subjected to a test of contextual or domain relevance. The Delphi method helps identify consensus opinion on critical factors, from a group of experts on an issue by conducting interrogative communications, as a bases for decision making or further analysis (Chan, Yung, Lam, Tam & Cheung, 2001). This approach is used in order to isolate factors that are truly representative of situation in the environment under examination. Table 1 show a sample rating form that can be used for this expert rating exercise.

Table 1: Guide for Professional Contextual Rating

		4	3	2	1	0
S/No	ITEMS	ES	HS	S	LS	NS
1	A					
2	B					
3	C					
4	D					
5	E					
6	F					
7	G					
8	H					
9	I					
10	J					

Where, **ES**, is Extremely Significant; **HS**, is Highly Significant; **S**, is Significant; **LS**, is Low Significance, and; **NS**, is Not Signify.

Extraction of contextually relevant mobility influencing factors from expert opinion

As a prerequisite to extraction of contextually relevant factors, the expert ratings should be subjected to an inter-rater consistency test using Cronbach's Alpha or any other suitable test. This is needed to ascertain whether the instrument is measuring what it purports to measure. Once the result of Cronbach's Alpha test is satisfactory, the weighted mean of ratings for each factor or attribute can then be calculated, as a way of further harmonizing expert opinion on the factor reduction exercise. Iteratively, a cut – off point for relevance and non-relevance need to be established. Usually factors rated in Likert scale as in Table 1, rely on calculated cut-off points to determine whether an item is significant or not (Morenikeji, 2006). The cut-off point is given by the arithmetic mean of individual weights. These preceding tasks will enable the extraction of factors considered contextually relevant to the study area from the general list of factors rated by the professional screeners by comparing calculated weighted mean values to derived mean cut-off point.

Thematic Categorization of Contextually Relevant Mobility Influencing Factors by Attribute similarities

Isolated factors above are in turn characterized based on attribute similarities to create thematic groups. For instance, factors with attributes describing road network characteristics are listed under such a thematic area. Characterization is required to justify group by group comparison of results, since factors work in unison to shape the perception of individuals, as attested to by Solowasky (2014). The groupings are then used to design the template for the entire zone's mobility influencing factors perception survey, as shown in Table 2.

Table 2: Rating Guide with Thematic Categorization of Urban Mobility Influencing Factors

S/No	ITEM S	5	4	3	2	1
		SP	P	NPN	N	SN
Category A	<i>Network Characteristics</i>					
1	A					
2	B					
3	C					
Category B	<i>Development Characteristics</i>					
4	D					
5	E					
6	F					
7	G					
8	H					
Category C	<i>Density of opportunity</i>					
9	I					
10	J					

Where, **SP**, is Strongly Positive; **P**, is Positive; **NPN**, is Neither Positive nor Negative; **N**, is Negative, and; **SN**, is Strongly Negative respectively.

Conduct of General Mobility Influencing Factors Perception Survey

Following categorization of contextually relevant mobility influencing factors and development of survey template, a general traveler mobility influencing perception survey is then carried out, following a credible sampling design, culminating from adequate consideration of total number of official spatial sub units and their characteristics. The extracted and categorized contextually relevant factors are presented to individual traveler selected at random to rate perceived effect of mobility influencing factors, using the template labeled as Table 2.

Ranking Contextually Relevant Factors

On receipt of ratings from general respondents' survey, factor ranking to establish order of importance is then done. The tradition has been to first arrange the observations either from the smallest to the largest or from the largest to the smallest, and assign them the positive integers as ranks (Gibbons, 1973). Hence, the calculated weighted mean of entries for each factor can be compared to determine which factor returns the highest or lowest weighted mean value, and which factors are in-between. Based on this, factors are then arranged in descending order of importance, such that the highest calculated weighted mean value ranks first (1st) and the lowest value last. The resultant arrangement then defines factor rankings based on perceived effect by respondents, as in Table 3.

Table 3: Rank Position of items

Items	Rank Position
A (Highest Weighted Mean)	1st
B	2nd
C	3rd
D	4th
E	5th
F	6th
G	7th
H	8th
I	9th
J (Lowest Weighted Mean)	10th

Noteworthy is the fact that, the resulting weighted mean values are not in this case used to accept or reject factors, since all the factors have been deemed contextually relevant by expert opinion. The weighted mean values are instead used to rank contextually relevant factors according to perceived level of significance to specific spatial sub-unit.

Assignment of Accentuated factor Rank Order of Importance Points (ROIP)

Ascertaining measures of relative significance of indicators can be a concern in studies that employ weights or index (Rygel, O'sullivan and Yarnal, 2006). In practical applications, it is useful to convert rankings into points that reflect the relationship or position of the observations relative to one another in terms of their magnitude (Oyeka, Osuji and Nwankwo, 2013). Magnitude depicts greatness of size, volume or extent, usually represented by a number assigned to mathematical quantity, which points to its relative status. Thus, the simplest approach to ascertain this is value comparison along a defined scale. To achieve this, Rank Order of Important Points are assigned such that, numerical value of awarded points reflects true order of importance. For instance, the 1st ranking factor out of ten (10) observations may be assigned 10 points as a measure of its higher significance over the 10th ranking factor, with 1 point, hence accentuating the status of the 1st ranking factor appropriately, as illustrated in Table 4. The maximum and minimum point values are reflective of the number of observations being considered in this particular case; this can change according to the number of factors under consideration. It must be noted that, the points do not represent a scale of importance - they are employed only to show the intensity with which factors have been perceived to be positively affecting respondents' mobility in the specific case described. More so, the action also serves to simplify the next step that is Index Equivalent Derivation.

Table 4: Rank Order of Important Points

Items	Rank Position	Rank Order of Important Points
A	1 st	10 points
B	2 nd	9 points
C	3 rd	8 points
D	4 th	7 points
E	5 th	6 points
F	6 th	5 points
G	7 th	4 points
H	8 th	3 points
I	9 th	2 points
J	10 th	1 Point

Derivation of Factor Index Equivalents (IE) from Accentuated Rank Order of Important Points (ROIP)

Context, subjectivity and their effect on outcomes of weighted or indexed inputs are usually a source of worry. Another challenge of weighting or index derivation and aggregation is how to deal with their different dimensions (Mingshun, 2002). To resolve this, several methods of weighting have been developed, each favoured for different purposes and targets. Bearing this in mind, the ratio method of weighting was adopted to convert Accentuated Rank Order of Importance Points to Index Equivalents (IE) for each factor. This method was chosen for its simplicity and effectiveness. It entails calculating index equivalent (IE) for each factor, using normalized Accentuated Rank Order of Importance Points (ROIP). Normalization scales all numeric variables in the range [0, 1] (Saitta, 2007), without units and disregarding physical dimensions, thereby enabling direct comparison of values. Against this backdrop, Accentuated Rank Order of Important Points (ROIP) is used as the bases of calculating corresponding Index Equivalents for each rank position. This is achieved by dividing individual ROIP of each factor by the sum of all ROIPs, this ensures that values are normalized, thereby eliminating bias stemming from differing dimensional attributes of factors. The resulting value becomes the working Index Equivalent for a particular rank position. This approach is necessary to justify individual IE value and its derivation. Normalization was achieved by applying Equation 1:

$$IE_i = \frac{ROIP_i}{\sum ROIP} \quad \dots (1)$$

The general form of equation (1) is shown in Equation (2), applicable when multiple cases are being considered in succession.

$$IE_i = \frac{ROIP_i}{\sum ROIP} \quad i = 1, 2, 3, \dots n \quad \dots (2)$$

Where, **IE** is calculated Index Equivalent for a specific factor; **ROIP_i** is Rank Order of Important Points of the factor under consideration; **ΣROIP**, represents sum of individual Rank Order of Important Points of all factors, see Table 5. After the determination of Index Equivalent of Accentuated Rank Order of Importance Points, the corresponding value for each factor is then entered accordingly. Note however that, where there are ties in Rank Positions, that is, when two or more items turn up with equal weighted means resulting into identical Rank Position, such as

having three cases of 2nd or any other position. It follows that there shall be no 3rd and 4th ranked factors, but, the appropriate IEs of the occurring Rank Position must be recorded in each case. Tables 5 and 6 depict sample Index Equivalents entry rules for distinct rank position cases and cases with ties.

Table 5: Sample Index Equivalent of ranks when all rank positions are distinct

Items	Rank Position (RP)	Accentuated Rank Order of Importance Points (ROIP)	Index Equivalent (IE)
A	1 st	10 points	0.182
B	2 nd	9 points	0.164
C	3 rd	8 points	0.145
D	4 th	7 points	0.127
E	5 th	6 points	0.109
F	6 th	5 points	0.091
G	7 th	4 points	0.072
H	8 th	3 points	0.055
I	9 th	2 points	0.036
J	10 th	1 point	0.018
Total		55	1.000

Table 6: Sample Index Equivalent entry style when there are ties in rank positions

Items	Rank Position (RP)	Accentuated Rank Order of Importance Points (ROIP)	Index Equivalent (IE)
A	1 st	10 points	0.182
B	2 nd	9 points	0.164
C	2 nd	8 points	0.164
D	2 nd	7 points	0.164
E	5 th	6 points	0.109
F	6 th	5 points	0.091
G	7 th	4 points	0.072
H	8 th	3 points	0.055
I	9 th	2 points	0.036
J	10 th	1 point	0.018
Total		55	1.000

It is necessary to mention that, other suggestions for breaking ties are available, such as dropping tied observations, if they are few, or by assigning tied observations randomly into groups to which samples may have been dichotomized, or assigning observations tied in one value the mean rank of tied observations (Siegel, 1956; Hollander and Wolfe, 1999; Oyeka and Uche, 2009). This work

maintains each ranks IEs at this stage because each factor may end up contributing to separate categories, and not necessarily the same thematic area.

Synthesizing Index Equivalents into Mobility Environment Outlook

An index provides an empirical and numerical basis for categorizing, comparing and evaluating performance. The measures that constitute an index are generally referred to as indicators. Indicators jointly summarize a system or indicate its' status (Giorgos and Gillian, 2005). The task of aggregating sub units Factor Index Equivalent into one Mobility Support Level Index (MSLI) for a defined spatial unit involves the successive computation of:

- i. Average Category Index Equivalent (ACI);
- ii. Spatial Sub Unit Mobility Environment Rating (xMER); and
- iii. Mobility Level Index (MLI)

Where (x) identifies a specific spatial sub unit. It is a stepwise procedure where the outcome of initial occurring stage provides input for the subsequent one.

Stage 1: Derivation of Average Category Index Equivalent (ACI)

Average Category Index (**ACI**) denotes the average IE of a thematic area. It is given by establishing the arithmetic mean of IEs of all factors in the thematic area. The comparable mathematical connotation is presented in Equation (3).

$$ACI_m = \frac{\sum_{i=1}^n IE_{mi}}{n}, \quad i = 1, 2, 3, \dots, n \quad (3)$$

Where, **ACI_m**, is the Average Category Index Equivalent of a thematic group; **IE_{mi}** are individual Factor Index Equivalents; **m**, identifies a specific factor, i.e. m = a, b, c, ..., z, as the case may be; **n** is the max of **i**, i.e. number of factors in a thematic area.

Stage 2: Computing Spatial Sub Unit Mobility Environment Rating Index (xMER)

As required, the Average Category Indices (ACIs) from Stage 1 are extracted and summed up. The resultant value becomes the Mobility Environment Rating Index (**xMER**) of a specific spatial sub – unit. This is a measure of the percept-based level of mobility support the sub unit offers. Equation (4) presents the mathematical expression.

$$xMER = \sum_{i=1}^n ACI_{mi} \quad i = A, B, C, \dots, n \quad (4)$$

Where, **xMER**, is the calculated Mobility Environment Rating Index of a specific spatial sub unit; **ACI_{mi}**, is the Average Index Equivalent of a specific thematic area; and **m**, defines a specific thematic area, i.e. m = a, b, c, ..., z, as the case may be. The resultant values will look as denoted in Table 7

Table 7: xMERI for a Hypothetical Spatial Zone

S/No	ITEM S	Rank Order (RO)	Index Equivalent (IE	ACI
Category A	Network Characteristics			
1	A	1 st	0.182	0.164
2	B	2 nd	0.164	
3	C	3 rd	0.145	
Category B	Development Characteristics			
4	D	4 th	0.127	0.091
5	E	5 th	0.109	
6	F	6 th	0.091	
7	G	7 th	0.072	
8	H	8 th	0.055	
Category C	Density of opportunity			
9	I	9 th	0.036	0.027
10	J	10 th	0.018	
			xMLI	0.282

Stage 3: Aggregating Sub - Unit Mobility Environment Rating Index (xMERI) into Spatial units Mobility Level Index (SMLI)

The Spatial units Mobility Level Index describes the overall mobility qualities as perceived by the respondents. There are two (2) approaches to deriving Spatial unit Mobility Level Index (SMLI). Approach one (1) simply uses the arithmetic mean of aggregated **xMERI** scores of sub – units of an identified zone, as the aggregate estimate, mathematically illustrated as in Equation (5).

Approach 1:

$$SMLI = \frac{\sum_{i=1}^n xMERI_i}{n}, \quad i = 1, 2, 3, \dots, n \quad \dots\dots (5)$$

Where, **SMLI**, is the calculated Mobility Level Index; **xMERI_i**, is the sum of all Mobility Level Index of spatial sub-units; and **n** is the max of **i**, i.e. number of sub units. Because approach one tends to becloud some useful information, a more comprehensive alternate approach is also presented. Approach (2) utilizes Average Factor Index Equivalents (AFIE) to compute aggregate spatial unit's Category Index Equivalents (SCIE), as a precursor to determining SMLI. The first part of this exercise is achieved by applying Equation (7), to generate the inputs for Equation (8) respectively.

In practice, individual Index Equivalent of a factor as they occur for each city sub unit are summed up and averaged, revealing the Spatial unit Average Factor Index Equivalents (SAFIE). The results are then employed in determining Spatial unit Average Category Index Equivalents (SACI), following similar steps as described in Equation (3) above. SAFIE is determined as given in Equation (6).

$$SAFIE_m = \frac{\sum_{i=1}^n FIE_{mi}}{n}, \quad i = 1, 2, 3, \dots, n, \dots \quad (6)$$

Where, **FIE_{mi}**, is the Index Equivalent of a specific factor for a specific sub – unit; **SAFIE_m**, is the Spatial units' Average of Factor Index Equivalents of a Factor in all sub-units; **m**, identifies specific sub unit, i.e. m = a, b, c, z;; **n** is the max of **i**, i.e. number of spatial sub-units. Furthermore, the overall Average Category Index Equivalent (ACI) for each thematic area is then calculated. This is given by averaging the sum of calculated (**SAFIE**) for each theme group, as depicted in Equation (7).

$$SACI_m = \frac{\sum_{i=1}^n SAFIE_{mi}}{n}, \quad i = a, b, c, \dots, n \dots (7)$$

Where, **SAFIE_{mi}**, is Spatial units' Average Factor Index Equivalent of a specific factor; **SACI_m**, is City scale Average Category Index for a thematic sub- unit; **m**, identifies specific thematic category, i.e. m = a, b, c, z, as required; and **n**, is the number of factors in the category under consideration.

Stage 4: Aggregating Spatial units' Mobility Level index

Accordingly, Spatial units Mobility Level Index (**SMLI**) is then derived by summing up Spatial units' Average Category Index Equivalents (SACI) for all thematic areas, that is;

$$SMLI = SACI_{mi}, \quad i = a, b, c \dots n \quad (8)$$

Where, **SMLI**, is the resultant Mobility Index; and **ΣSACI_{mi}**, is the sum of Average Category Index Equivalents for all thematic areas. The output typically shows contributions of factors in rows and columns, for easy comparative analysis. As exemplified in Table 7. A summary of the iterative procedure described above is typified in Fig. 1.

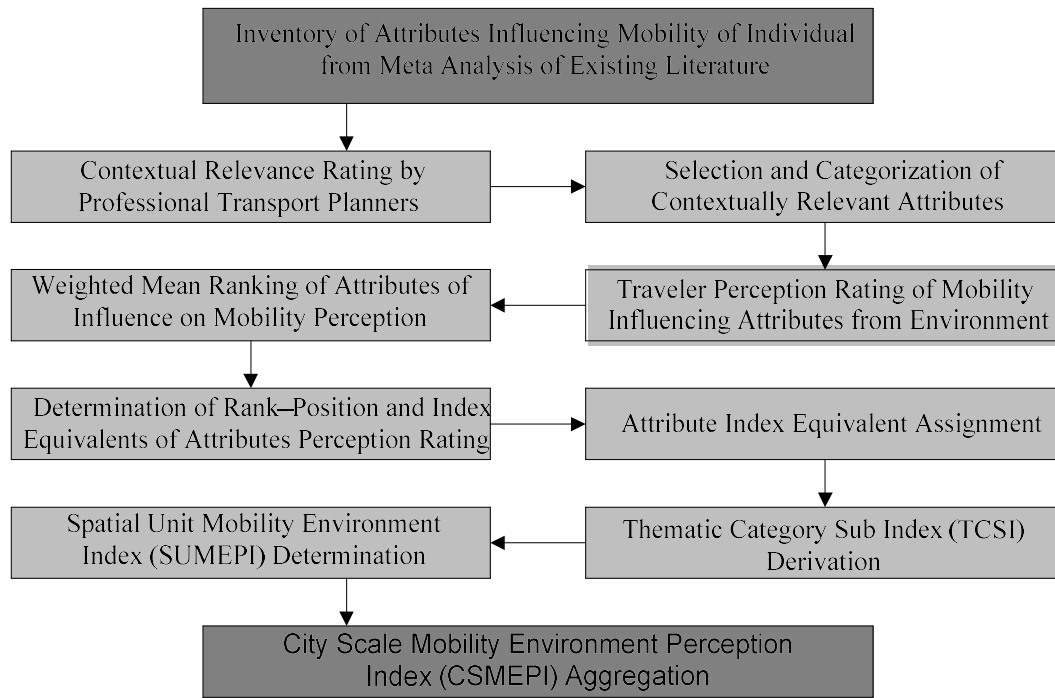


Figure 1: Schema for Rating Mobility Environment with Traveler Perception

Index Interpretation and Judgment rules

As is common with index-based constructs, interpretation tables are used to correlate the calculated or derived value(s) with a range of possible positions along a predetermined continuum of grades (Mingshun, 2002, Fabiyi, 2006; Zaly, 2010). This work adopts the same technique, considering the theoretical maximum and minimum values accruable in the best- and worst-case scenarios, where the mathematically attainable maximum and minimum values for derived IE range is used. The resultant composite index is then compared with values on the interpretation table, as in Table 8.

The premise is that mobility level of a spatial unit increases as Mobility Level Index (MLI) or (SMLI) tends towards the maximum achievable xMLI value, which in this case is (0.546), while mobility level of a spatial unit decreases as Mobility Level Index (xMLI) or (SMLI) tends towards the minimum (0.054). The figures literarily denote the degree to which a spatial unit enhances or inhibits mobility. Therefore, it is expected that the higher the xMLI, the higher the perceived support a spatial unit provides for mobility and vice versa. Hence, the xMLI value of (0.282) derived for the hypothetical case in sub section 3.9.2, connotes a grade “1” “Fair” mobility level, meaning that systematic improvements to mobility influencing factor attributes that might be keeping the SMLI low is required. Note that, the ranges of values on the interpretation table are not sacrosanct, they can change as number of factors change for different situations. The main aim is for comparability in a defined context.

Table 8: Spatial units' Mobility Level Index Interpretation Table

MLI Value Range	Descriptive Change Level Indicator	MLI Improvement Indicator	Interpretation
0.541 – 0.546	2	10	Excellent Mobility Support Level
0.487 – 0.540	1	9	
0.433 – 0.486	2	8	Good Mobility Support Level
0.379 – 0.432	1	7	
0.325 – 0.378	2	6	Fair Mobility Support Level
0.271 – 0.324	1	5	
0.217 – 0.270	2	4	Inadequate Mobility Support Level
0.163 – 0.216	1	3	
0.109 – 0.162	2	2	Restrains Mobility
0.054 – 0.108	1	1	

The interpretation table was developed using “theoretical minimum and maximum achievable points” method, as described by Mingshun, 2002 and Oluseyi, 2006. From Table 5, it can be deduced that the minimum and maximum achievable *IEs* are 0.018 and 0.182 respectively, meaning that the minimum *MSI* possible for a thematic category, for instance “network characteristics” is 0.018. Therefore, the minimum for a zone is deduced by multiplying 0.018 by the number of thematic categories (x), which in this example are 3, so, *Minimum MSI possible for thematic category multiplied by Number of Thematic Categories = Minimum MSI possible for such a zone* ($0.018 \times 3 = 0.054$ index points).

Similarly, from Table 5, the maximum achievable *IE* is calculated to be 0.182, which translates to a maximum 0.546 maximum *MSI* possible for a thematic category. Hence, *Maximum MSI possible multiplied by Number of Thematic Categories = Maximum MSI possible for that zone* ($0.182 \times 3 = 0.546$ index points).

Next, the number of times a zone has to leap from “Minimum to Maximum Achievable Index” points is calculated by dividing the number of needed leaps from “Minimum to Maximum.” Which is given by *Maximum Achievable Index points divided by Minimum Achievable Index points = Number of leaps from Min to Max condition*, arithmetically shown as $0.546 / 0.054 = \approx 10$ times, the resulting figure is described as “*MSI Improvement Indicator*” in Table 8. From which the possible number of “Descriptive Change Levels” a zone needs to go through to advance from “Minimum to Maximum Achievable Index” points are determined. The “*MSI Value Range*” define the “Minimum and Maximum” value ranges for each level, this help show progress even within the same interpretation zone, by marking the upper and lower limits. Five interpretation zones are deducible; each with its upper and lower zones that marks the transition from restraining to exceptional mobility support.

Functional Applications of Perception Based Mobility Level Index

The main reason for this tool is to use minimal, cost effective and easily gathered data to estimate urban mobility levels in cities without standard, incrementally updated data bases for mobility assessments. Secondly, it is expected that the problem of indeterminate urban mobility levels would start getting resolved, thereby reducing the hitherto subjective, even random nature of dealing with mobility issues in data deficient scenarios. City managers can employ the MLI tool in identifying where, when and what kind of interventions are needed to improve mobility as cities evolve. With a framework like MLI, a much more focused approach to improving urban mobility support qualities and ease of mobility can be crafted for identified settings. MLI can also provide urban managers with an understanding of the kind of environment preferred by citizens within the planning district. More so, the tool can help classify and rate environmental challenges to mobility as perceived by cross sections of the population. Intervention prioritization and budgeting matters are also expected to become even more straightforward and objective. Ultimately, MLI tool will enable comparative analysis of mobility levels within and between spatial units of interest, such as neighbourhoods, districts and cities. The framework can be used to identify lagging districts of cities or compare one city to another.

Data collected across constituent blocs of an area can be queried to achieve other varying objectives. The overall requirements of attaining stated mobility level targets for different situations can easily be identified and pursued. The relative simplicity of the tool makes leveraging outputs or results for policy rationalization more realistic. The tool is likely to be more acceptable to policy makers who seem to loath highly technical approaches that usually require specialized knowledge to interpret. It thus becomes necessary to try options such as the MLI technique in gauging mobility level, not only for its simplicity, but also because it captures aspects of human mobility complexities, alongside being useful where data problems are evident. Parsimonious techniques such as this are therefore essential, if urban mobility problems and their secondary, tertiary and quaternary offshoots are not to persist. For further improvement, a simple computer application or programme can be developed for each spatial entity, to reduce the iterative nature of the process and to minimize error.

Conclusion

Valuable as abstract models are in evaluating mobility, they still cannot mimic the movement of people to every little detail (Hong, 2010). They are especially incapable of capturing the real-life mobility complexities individual's experience. First, this work presents an alternative mobility appraisal tool to complex data hungry models, which uses easily gathered data to facilitate realistic situational mobility evaluations, thus, permitting some measure of conscious management to begin in secondary data deficient settings. It does this by providing an alternate method of feeding the basic planning process with needed information to proceed rationally to the next phase of planning. The study also bridges the need gap for a parsimonious technique of appraising mobility, from the angle of mobility environment attributes perception, where problems of data inadequacy or availability bedevils the application of standard mobility modeling techniques. This serves to reduce the negative implications of indeterminate and indescribable mobility situations, characteristic of cities in developing nations, thereby enabling reasonable evaluations as a basis for local solutions and interventions. The tool's usage of individual percept of mobility influencing attributes enables a decent capture of some measure of mobility complexity determinants in the estimation of mobility environment perception index, thereby

prioritizing the real essence of mobility planning, which is meeting Instrumental Activities of Daily Living (IADLs), an important determinant of quality of life.

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References

- Aderamo, A. J. (2000). City Planning and Management Techniques. In Jimoh and Ifabiyi (eds). *Contemporary Issues in Environmental Studies*. University of Ilorin, Ilorin.
- Azevedo, T.S., Bezerra, R.I., Campos, C.A., and de Moraes, L.F., 2009. An Analysis of Human Mobility using Real Traces. Wireless Communications and Networking Conference, WCNC 2009. IEEE. (2009), 1-6. Federal University of Rio de Janeiro.
- Bentley, I., Alan, A., Murrain, P, McGlynn, S., and Smith, G., 1985. *Responsive Environments: A Manual for Designers*. The Architectural Press Limited, London.
- Calabrese, F., Di Lorenzo, G. and Ratti, C., 2010. Human Mobility Prediction based on Individual and Collective Geographical Preferences. *Intelligent Transportation Systems (ITSC)*, 13th International IEEE Conference. 312 – 317.
- Carmona, M., Heath, T., Oc, T. and Tiesdell, S., 2003. *Public Places Urban Spaces: The Dimensions of Urban Design*. Architectural Press, Oxford – England.
- Chan, A.P.C., Yung, E.H.K., Lam, P.T.I., Tam, C. M and Cheung, S.O. 2001. Application of Delphi method in selection procurement systems for construction projects. *Construction Management and Economics*, Vol. 19, Issue 7, Pg. 669 – 718
- Cherry, K. 2010. The Everything Psychology Book: An Introductory Guide to The Science of Human Behavior. 2nd Edition, Adams Media
- Gibbon, J.D. 1973. Non-Parametric Statistical Inference. McGraw-Hills book Company, New York.
- Giorgos, M, Gillian, A and Kate, B., 2005. *Modeling Rurality using Spatial Indicators*. Available at: <http://iisd.ca/measure/default.htm>.
- Hollander, M. and Woife, D.A. 1999. Non-Parametric Statistical Methods, (2nd edition). Wiley-Inter Science, New York.
- Hong, S., 2010. *Human Movement Patterns, Mobility Models and Their Impacts on Wireless Applications*. A dissertation submitted to the Graduate Faculty of North Carolina State University in partial fulfillment of the requirements for the Degree of Doctor of Philosophy Computer Science Raleigh, North Carolina.
- Isaacman, S, Becker, R., Caceres, R., Martonosi, M., Rowland, J, Varshavsky, A, and Willinger, W. 2012. Human Mobility at Metropolitan Scales. *Mobisys'12*
- Kovalik, C. and King, M.E. 1998. Visual Literacy, Available: <http://www.educ.kent.edu/community/VLO>; Retrieved 27th November, 2014
- Mingshun, Z., 2002. *Measuring urban Sustainability in China*. Thesis Submitted in Partial fulfillment of the Award of PhD to the Institute for Housing and Urban Development Studies (IHS) and Erasmus University, Rotterdam, the Netherlands.
- Morenikeji, W. 2006. *Research and Analytical Methods*, Jos University Press Ltd, Jos – Nigeria.
- Noulas, A, Scellato, S, Lambiotte, R, Pontil, M, and Mascolo, C., 2012. *A Tale of Many Cities: Universal Patterns in Human Urban Mobility*. Available from: PLoS 7(5):e37027. DOI:10.1371/journal.pone.0037027.

- Ni, D., John, D.L. Guin, A, and Williams, B, M., 2004. Systematic Approach for Validating Traffic Simulation Models Transport Research Records: Journal of the Transportation Board, No. 1876, TRB, National Research Council, Washington, DC., pp. 20 – 31
- Ogunsaya, A. A., 1986. Some Remarks on the Use of the Conventional Modeling for Transportation Planning in Developing Countries. *Journal of the Nigerian Institute of Town Planners*, Vol. VI and VII pp. 71 – 85.
- Oluseyi, F.O., 2006. Analysis of Inter – Connectivity Levels of Urban Street Networks and Social Interactions in Enclosed Neighbourhood in Johannesburg RSA. *Humanity and Social Sciences Journal*, 1 (1): 79-95.
- Oyeka, C.A. Osuji, G.A and Nwankwo, C.C. (2013). Simplified Method of Rank Determination In Rank Order Statistics. *Mathematical Theory and Modeling*. Vol.3, No.14, 50.
- Oyeka, C.A. and Uche, A. 2009. A Method of Analyzing Paired Data Intrinsically Adjusted for Tie. *Global Journal of Maths and Statistics*. Vol. 1, pp.1- 6
- Rygel, L., O’sullivan, D., and Yarnal, B., 2006. *A Method for Constructing a Social Vulnerability Index: An Application to Hurricane Storm Surges in a Developed country. Mitigation and Adaptation Strategies for Global Change*. 11: 741–764. Springer. DOI: 10.1007/s11027-006-0265-6
- Saitta, P., 2007. Standardization vs. Normalization. *Data Mining Research*. [www.dataminingblog.com/standardization - vs -normalization](http://www.dataminingblog.com/standardization-vs-normalization).
- Shittu, A.O. (2014). Towards Quasi-formal Management of Paratransits in Informal Transport Dependent Cities of Nigeria. *IOSR Journal of Humanities and Social Science (IOSR-JHSS)*. 19(12), Ver. IV (Dec.), pp. 75-80. DOI: 10.9790/0837-191247580
- Siegel, S. 1956. *Non - Parametric Statistics for Behavioral Sciences*,” McGraw-Hill Book Company, New York.
- Sokolowska, K. 2014. Determinants and Perceptions of Social Mobility in Poland, 1992 – 2008, *Contemporary Economics*, Vol. 8, No. 1, pp. 89 – 109.
- Wang, S., 2011. *Analysis of Human Mobility Modeling Methods*. Seminar presented at the Florida Institute of Technology and Computer Science. USA.
- WBCSD, 2004. *Mobility 2030; Meeting the Challenges of Sustainability*. Geneva: The Council.
- Zaly, M., 2010. Rating Pedestrian Facility with P – Index and The Application of Google Map. *Centre for Innovative Planning and Development, Monograph No.8; Universiti Teknologi Malaysia*.