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A fuzzy approach for assessment of smart socio-cultural attributes of a historic urban landscape: Case study of Alwar walled city in India

Mani Dhingra *, Subrata Chattopadhyay

Department of Architecture & Regional Planning, IIT Kharagpur, 721302, West Bengal, India

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ABSTRACT

Smartness is a vague concept with different meanings for different people. It is imperative to harness the latent potential of existing settlements for an inclusive smart urban development. The study aims to assess the socio-cultural attributes of an Indian historic urban landscape with a thriving residential culture. Since data collection of neighborhood-level urban communities is not feasible in India, a structured questionnaire was used to conduct household surveys. Such real-world phenomena have inherent imprecision and ambiguity associated with human judgments. Therefore, the survey items are assumed as fuzzy linguistic variables, and the raw dataset is transformed into triangular fuzzy numbers. Fuzzy arithmetic and weighted averaging operators are applied for the hierarchical evaluation of indicators and variables. A robust algorithm is used for the dimension reduction of a fuzzy coded dataset while dealing with subjective responses. The aggregated fuzzy scores show an overall better performance of traditional communities with respect to their socio-cultural attributes, such as a sense of safety and collective efficacy. The application of fuzzy logic in urban planning and allied behavioral studies can effectively and pragmatically deal with the inherent uncertainties in a humanistic system. Future researchers may explore fuzzy multi-criteria evaluation approaches for ordinal scale datasets.

1. Introduction

Many countries around the globe, including India, are adopting the smart city mantle to tackle urban issues for self-promotional purposes (Hollands, 2015). However, smart interventions are awkwardly fixed in an existing socio-spatial setting without considering its historical and geographical context (Neirotti, De Marco, Cagliano, Mangano, & Scorrano, 2014; Shelton, Zook, & Wiig, 2015; Yigitcanlar, 2015). The concept of smart cities emerged with the Kyoto Protocol in 1998 with a strong focus on environmental sustainability (Dhingra & Chattopadhyay, 2016, 2017). Post-2000, global attention shifted to digital interventions in urban areas, and with the Europe 2020 strategy, the overall narrative again turned back to the agenda of urban sustainability (Aurigi & Odendaal, 2020). This entire process of building smart cities is strongly criticized because of its fragmented strategies, top-down approaches, and poor adaptation to the local needs (Angelidou, 2017; Martin, Evans, & Karvonen, 2018).

Many scholars such as Albino, Berardi, and Dangelico (2015), Angelidou (2014), Castelnovo (2016), Claire., Catherine., Thorne, and Griffiths (2014), Deakin and Al Waer (2011), Glasmeier and Christopherson (2015), Harrison (2017), and Prado, Costa, Furlani, and Yigitcanlar (2016) urged to include communities, their socio-cultural aspects, and local context in the smart urban development framework. Also, international organizations such as UNESCO and the World Bank advocate equitable ways of the sustainable revitalization of old cities and their communities. Authors acknowledge that a smart city should promote a lifestyle aligned to local cultural values, social interaction, historical lineage, cultural identity, sense of community pride, and belongingness to strengthen the local narrative and social capital (Prado et al., 2016).

There is a dire need to integrate socio-cultural aspects in the smart urban development framework to elevate the inherent smartness of a Historic Urban Landscape (HUL) (Claire. et al., 2014; Shelton, Zook et al., 2015; Yigitcanlar, 2015). This study defines a smart city as an urban community that improves the quality of life and well-being of its citizens, adopts sustainable urban planning practices, and aims at the

* Corresponding author.
E-mail address: ar.manidhingra@gmail.com (M. Dhingra).

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inclusive growth of its people (Bednarska-Olejniczak, Olejniczak, & Svobodová, 2019; Dhingra & Chattopadhyay, 2016; Garau & Pavan, 2018; Romanelli, 2020; Trindade et al., 2017). The study assesses the relevant urban attributes in a traditional walled city in India to understand its hidden potential.

The authors have conducted experts' interviews, focus group discussions, reconnaissance, and household surveys in a historic walled city of Alwar located in the state of Rajasthan in India. Such social and behavioral research is inherently complex, inconsistent, and ambiguous (Arfi, 2013; Herrera, Herrera-Viedma, & Verdegay, 1998; Klir & Yuan, 1932; Niskanen, 2004; Simo & Gwét, 2018). Their results are usually estimated through approximate reasoning of feelings, behaviors, expressions, and personal opinions of targeted respondents acquired with the help of linguistic variables (Vonglao, 2017; Zadeh, 1975). This study explores the techniques of fuzzy arithmetic, aggregated fuzzy numbers, and robust reduction of a multidimensional ordinal dataset. The methodology attempts to address the inherent uncertainties in a social setting in a more effective and pragmatic manner.

2. Literature review

2.1. Fuzzy linguistic variables and smart urban attributes

Based on a comprehensive literature review and computational text analysis of smart city research, the key objectives of smart urban development are identified as high quality of life, sustainable economic growth, overall urban sustainability, social inclusion, and integrated citizen services. Under the aegis of this holistic vision, Smart Urban Attributes (SUAs) are identified as those features and characteristics of a settlement system that contribute to the overall objectives of sustainable, liveable, and inclusive urban development. Social and behavioral sciences, which involve the assessment of such qualitative and subjective attributes, commonly use survey-based methods for data collection (Strong, 2017). However, conventional statistical approaches are inappropriate to examine the imprecise linguistic variables, which are characterized by multiple shades of meaning (Chou, Liu, Huang, Yih, & Han, 2011; McNeill & Thro, 1994; Niskanen, 2004). Moreover, there are high chances of a significant loss of qualitative information during the aggregation process (Carifio & Perla, 2007; Emmenegger, Schraff, & Walter, 2014). Thus, the concept of fuzziness as a non-probabilistic kind of vagueness is more appropriate while dealing with the humanistic systems (Smithson, 1983; Zadeh, 1965).

A linguistic variable is a quintuplet denoted by $(L, S(L), U, G, M)$, where L is the name of the linguistic variable, $S(L)$ denotes the term set of L, which is the set of names that provide the linguistic values of L with each value being a fuzzy variable across a universe of discourse U, G is a syntactic rule for generating the names of the values of L and M is a semantic rule for associating meanings $M(L)$ to L (Arfi, 2013; Bede, 2013; Klir & Yuan, 1932). A fuzzy subset $\widetilde{A}$ is defined by a membership function $\mu_{\widetilde{A}}: U \rightarrow [0, l]$, which associates a degree of membership with each element x of U in the interval $[0, l]$ belonging to $\widetilde{A}$ (Zadeh, 1975). This means that membership function $\mu_{\widetilde{A}}$ maps the values of elements x in the universe of discourse U to the fuzzy set $\widetilde{A}$ with degrees of membership between 0 and 1. For example, if fuzzy set $\widetilde{A}$ consists of elements x which are closer to number 1, for $x \in U$ given by $\{1, 2, 3, 4, 5\}$, then $\mu_{\widetilde{A}}$ can be written as $\{1/1, 2/0.8, 3/0.6, 4/0.4, 5/0.2\}$ i.e., as we move away from the number 1, the degree of membership keeps reducing by 0.2 for each consecutive number in $\widetilde{A}$.

The concept of fuzzy numbers play a fundamental role in formulating and representing quantitative fuzzy variables as linguistic concepts (Klir & Yuan, 1932). A Fuzzy Number (FN) is defined as a normal fuzzy set on the set of real numbers such that $\widetilde{A}: \mathbb{R} \rightarrow [0,1]$, with closed interval alpha-cut sets for $\alpha \in [0,1]$ and bounded supports (Bede, 2013). The linguistic expression of a FN is '*approximately M*', where M denotes any numerical value (Bandemer & Naether, 1992).

2.2. Fuzzy arithmetic techniques

The extension principle proposed by Zadeh (1975) provides a general method for extending the mathematical analysis to the fuzzy linguistic variables and perform real algebra with FNs (Emmenegger et al., 2014; Klir & Yuan, 1932; Villacorta, Masegosa, Castellanos, & Lamata, 2014). Triangular Fuzzy Number (TFN) is the most commonly used as they are easy and more definite for performing fuzzy arithmetic operations (Klir & Yuan, 1932; Rattanalertnusorn, Thongteeraparp, & Bodhisuwan, 2013; Tavana, Di Caprio, & Santos-Arteaga, 2015). TFN $\widetilde{A}$ is denoted by a triplet (a, b, c), where $a < b < c$ and is given by Eq. (1) (Martín, Román, & Gonzaga, 2018; Villacorta et al., 2014). Three values that define a TFN are a minimum at which the membership function is 0.0 (a), a kernel at which it is 1.0 (b), and a maximum at which it returns to 0.0 (c) (Hassall, 1999).

$$\mu_{\widetilde{A}} = \begin{cases} \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{c-x}{c-b} & b \le x \le c \\ 0 & otherwise \end{cases} \tag{1}$$

Fuzzy aggregation operators are useful for combining and summarising a finite set of fuzzy values into a single numerical value (Simo & Gwét, 2018). Formally, any aggregation operation on n fuzzy sets $(n \geq 2)$ is defined by a function $h: [0, 1]^n \rightarrow [0, 1]$ or $\widetilde{A}(x) = h(\widetilde{A}_1(x), \widetilde{A}_2(x), \ldots, \widetilde{A}_n(x))$, in which $\widetilde{A}_1, \widetilde{A}_2, ..\widetilde{A}_n$ are n fuzzy sets defined on universe of discourse U and $x \in U$ (Bandemer & Naether, 1992; Klir & Yuan, 1932). Function h should be continuous, symmetric, idempotent, and satisfy boundary conditions. Fuzzy intersections and unions do not qualify as aggregation operations, but averaging operations can be used as aggregation operations as they satisfy idempotency conditions (Emmenegger et al., 2014). One class of such averaging operations covering intervals between min and max operations is generalized means given by Eq. (2) (Bandemer & Naether, 1992; Chen, 1996; Klir & Yuan, 1932; Martín et al., 2018).

$$h_\alpha(a_1, a_2, .., a_n) = ((a_1^\alpha + a_2^\alpha + . . a_n^\alpha)/n)^{1/\alpha} \tag{2}$$

where α is defined as the parameter used to distinguish different means. Klir and Yuan (1932) uses limit theorem to show that for $\alpha \rightarrow 0$, function h_α converges to the geometric mean $(a_1 . a_2 \ldots, a_n)^{1/n}$ and for $\alpha = -1$, function h_α results into harmonic mean $\frac{n}{\frac{1}{a_1} + \frac{1}{a_2} + \ldots + \frac{1}{a_n}}$. For $\alpha = 1$, $h_1(a_1, a_2, .., a_n) = \frac{1}{n}(a_1 + a_2 + \ldots + a_n)$, which is the arithmetic mean. Another class of averaging operator is the Fuzzy Weighted Averaging (FWA) operator with $w = \{w_1, w_2, \ldots, w_n\}$ as the weighting vector is given by Eq. (3) for a $TFN(a_i, b_i, c_i)$ (Dubois & Prade, 1985; Simo & Gwét, 2018).

$$FWA(x_1, x_2, \ldots, x_n) = \Sigma_{i \in [n]} (w \odot \widetilde{x}_i) = \left(\sum_{i=1}^{n} w_i . a_i, \sum_{i=1}^{n} w_i . b_i, \sum_{i=1}^{n} w_i . c_i \right) \tag{3}$$

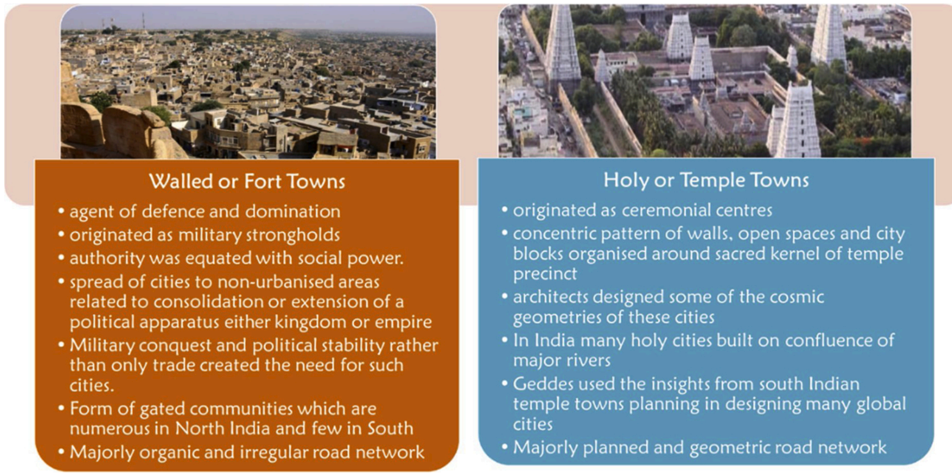


Fig. 1. Traditional cities categories.

where the ⊙ operator symbolizes extended product between weighting vector and TFN.

2.3. Multivariate data reduction

Classical PCA (CPCA) is the most popular multivariate method to reduce the dimensionality by finding k linear combination of the p original variables, such that $k < p$ for better interpretation of the dataset (Jollife & Cadima, 2016; Manisera, van der Kooij, & Dusseldorp, 2010). The Principal Components (PCs) correspond to the vectors in directions that maximize the variance of the projected data on this k linear combination (Alkan & Ganik, 2017). CPCA assumes all variables as numeric with linear inter-relationships, which is often not true in social sciences (Manisera et al., 2010).

Non-Linear PCA (NLPCA) is used as an alternative for datasets containing variables with unequal interval levels and non-linear inter-relationships (Linting & van der Kooij, 2012; Manisera et al., 2010). NLPCA monotonically transforms categorical variables in a statistically optimal way while maintaining the original order (Linting & van der Kooij, 2012; Meulman, Van Der Kooij, & Heiser, 2004). Robust PCA (RPCA) is another technique which decomposes a data-matrix into a sum of two components: a low-rank component associated with a general pattern and a sparse component associated with disturbances in the dataset (Jollife & Cadima, 2016).

2.4. Application of fuzzy logic

Linguistic terms, satisfaction degrees, perceived quality, and importance degrees are often vague (Chien & Tsai, 2000). Hence, various disciplines have adopted fuzzy logic to aggregate such imprecise human judgments. For instance, Martín et al. (2018) evaluated the delegates' satisfaction attending the academic conferences and Chen (1996) evaluated weapon systems using fuzzy arithmetic operations on TFNs. Cabitza and Ciucci (2018) fuzzified ordinal scales by assigning a TFN to each label in medical research. Similarly, Herrera et al. (1998), Tavana et al. (2015), Herrera-Viedma, Riera, Massanet, and Torrens (2014), Villacorta et al. (2014), Lalla, Facchinetti, and Mastroleol (2005) and Burhan Turksen and Willson (1994) quantified the survey responses using fuzzy logic.

Chou et al. (2011) and Aydin and Pakdil (2008) evaluated airline service quality using SERVQUAL method in which passengers' subjective perceptions and expectations are defined using a five-point Likert scale were converted into fuzzy numbers. Hassall (1999) argued that a respondent Likert score of 4 is a constrained choice in the range with 3 as the minimum and 5 as the maximum value. Vonglao (2017) also applied fuzzy logic to improve the Likert scale to measure combined scores of latent variables for which each question has a five-scale response: least, less, moderate, more, and most, with the scores for the scale being 1, 2, 3, 4, and 5, respectively.

Table 1
Case Selection Criteria.

	Criteria	Description
1	Size of town	Metropolis has migration as an important driving force diluting the essence of traditional communities, and medium-sized towns are preferred.
2	Moderate climate	neither too hot nor too cold climate
3	Historic urban landscape	Indian HUL typically characterized by traditional houses, streetscapes, water systems, living communities, traditional livelihoods, and social practices, clearly differentiating them from the rest of the city (Dhingra et al., 2017)
4	Urban origins	Originally developed as walled settlements
5	Residential culture	Local/traditional neighborhood patterns with living social and cultural values
6	Data-collection	Local language for surveys and logistics support
7	Regional significance	Prominent town in the past and present

3. Case study

The fabric of a historic town is not only characterised by its physical form and structure but also connects various attitudes and activities of a society. Kostof (1991) discussed two categories of traditional cities based on their origin, as shown in Fig. 1. During the medieval period in Indian history, a large number of kingdoms flourished, with either religion or military or politics forming the basis of city planning. The study intends to assess such a walled city in India where a traditional way of living, unique residential culture, a latent system of planning, characteristic physical and social fabric still prevails. The walled towns have a sensitive environment, with every micro-institution playing a significant role with a unique compact fabric (Mohan, 1992).

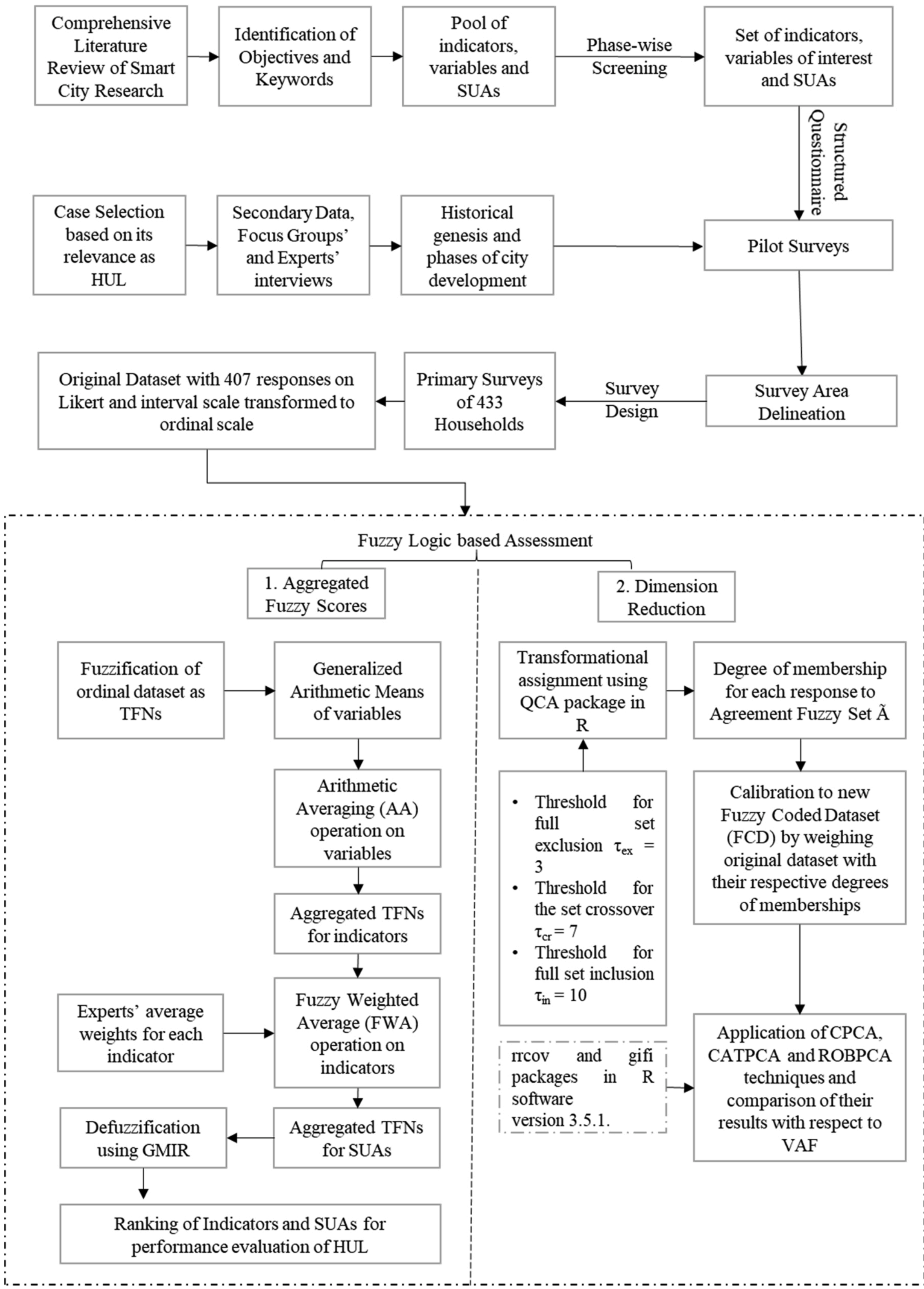


Fig. 2. Methodology adopted.
Source: authors.

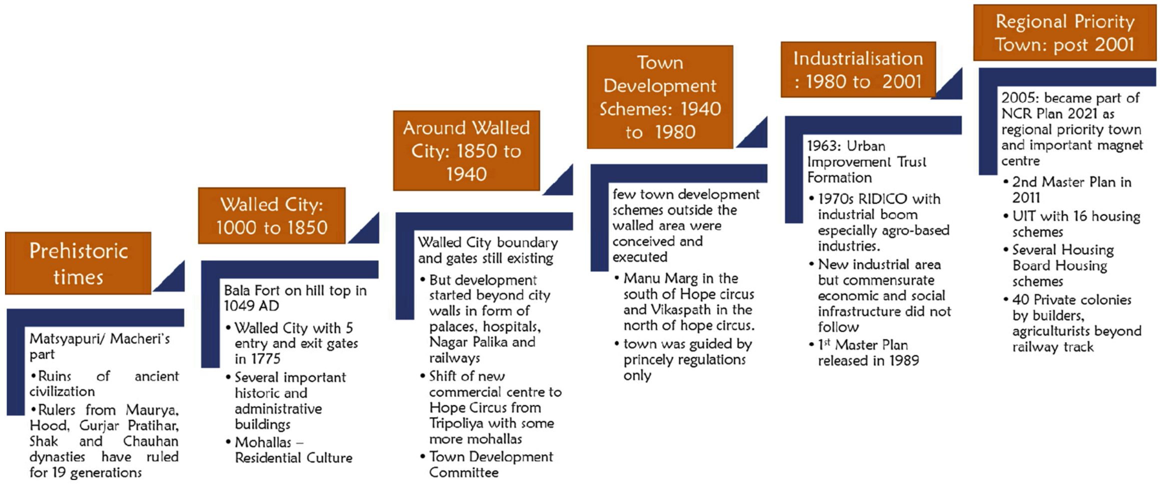


Fig. 3. Evolution of city.
Source: authors.

Based on the criteria mentioned in Table 1, the old walled city of Alwar in the north-eastern part of Rajasthan state is selected (Dhingra, Singh, & Chattopadhyay, 2016). The city is located at 27.57 °N; 76.6 °E, with an average elevation of 271 m bordered by Aravalli ranges on its west. It has a dry climate with hot summer, cold winter, and a short monsoon. As per Köppen's classification, it lies in BShw climatic zone (Semi-arid Steppe type). The town is midway between the national capital, Delhi, and the state capital, Jaipur. The total urbanized area is approximately 58.07×106 m^2, out of which the total developed area is 40.70×106 m^2, with a total population of 315,310 (Government of India, 2011). It is the third most populous district in the state, followed by Jaipur and Jodhpur (Town Planning Department, 2011).

During the British rule, it was a princely state with origins dating back to the Indus valley civilisation. The prehistoric evidence found by the Archaeological Survey of India (ASI) shows that the territory held a special historical and regional significance in ancient India (Dhingra & Chattopadhyay, 2016). The walled city of Alwar was laid out in 1775 CE based on ancient town planning principles under the foothills of Aravalli mountain ranges (Dhingra & Chattopadhyay, 2016; Dhingra, Kumar, Chattopadhyay, Singh, & Chattopadhyay, 2017). Historians KE Schwartzberg and Lucia Michelutti described Alwar as a folk region and a cultural geographical region, respectively.

The surrounding contiguous development of the city is less dense and is planned on a regular grid. The central core serves as the Central Business District of the city with traditional economic activities such as wholesale businesses, textiles, jewelry, handicrafts, and art industries. Historic neighborhoods locally known as mohallas portray the rich and unique Rajputana style of architectural elements such as Jalis (perforated walls), Jharokhas (shaded balconies), and courtyard-type of planning (Dhingra & Chattopadhyay, 2016; Dhingra et al., 2016, 2017). Presently, a traditional way of living is still prevalent in the historic core featuring rich tangible and intangible heritage (Dhingra & Chattopadhyay, 2016; Dhingra et al., 2016, 2017).

Alwar is the biggest town and a very busy trading center in north-eastern Rajasthan because of its location. It is an important counter magnetic centre of the national capital region, which further raises concerns about how the new urban development should deal with the traditional settlements (Dhingra et al., 2016). The language spoken is Hindi or Marwari, which is well versed with the authors, and logistic support such as accommodation and conveyance are easily available for conducting the surveys, which makes the data collection feasible.

4. Materials and methods

Fig. 2 shows the stepwise algorithm followed for the analysis of primary survey responses. A comprehensive literature review of existing smart cities research helped to formulate a working definition of smart city, which is more aligned towards human-centric approach of urban planning. An extensive keyword search identified a relevant set of socio-cultural indicators for the assessment of neighborhood-level urban communities in a HUL for achieving smartness. Some of these keywords are 'sustainable', 'liveable', 'inclusive', 'cultural', 'smart', 'social', 'neighborhoods', 'communities' and 'settlements'. A pool of around 347 indicators and 47 SUAs is derived under social, economic, environmental, mobility, living, governance, physical, and cultural dimensions. These are further screened based on seven criteria viz. relevance, specificity, redundancy, measurability, data collection feasibility, the spatial scale of reference, and number of times secondary sources cite it (Brown, 2009; Macdonald, 2016; Moore, 1950; Rice & Rochet, 2005; Selection of Indicators, 2020; The Social Report, 2010)

The case study is a typical example of an Indian HUL, for which secondary data, focus group discussion, experts' surveys, historical evolution, development of the present city form, and the statistical results of pilot surveys were analysed. Pilot surveys of around 52 respondents were conducted during 2017 within and around the core city area to delineate the final survey area. The final surveys were completed in 2019 for 433 households within the delineated area.

In the first phase of analysis, the ordinal scale responses were converted to TFNs to produce aggregated scores for each variable, indicator, and their comprising SUAs. Experts' weightages were used to calculate fuzzy weighted average scores of each indicator. These triangular fuzzy scores were further converted to crisp values with the help of defuzzification process. The second phase of analysis used transformational assignment assuming a linear degree of membership. Accordingly, the raw dataset was calibrated to a new Fuzzy Coded Dataset (FCD). Different PCA techniques were experimented with for multivariate

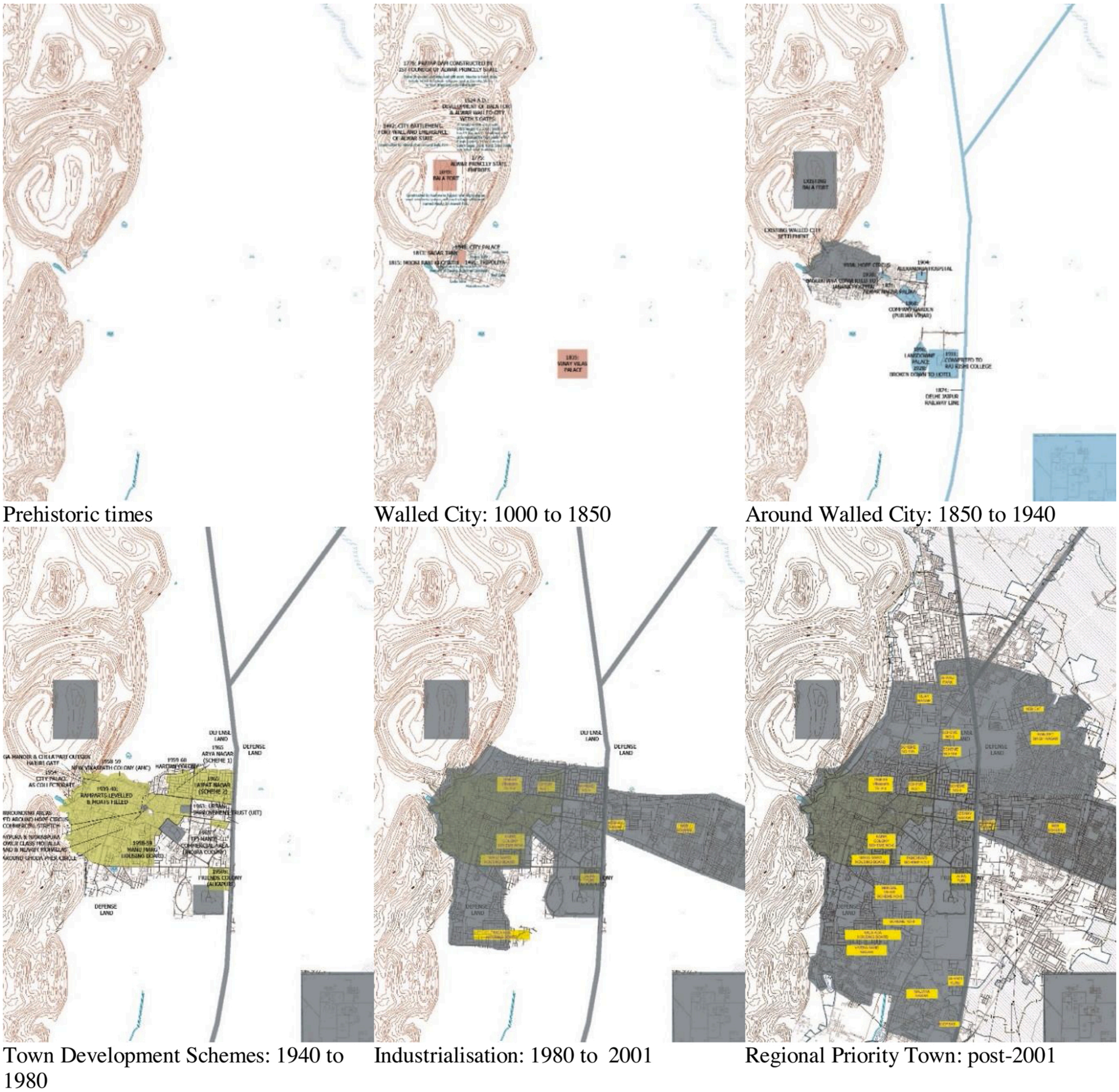


Fig. 4. Historical Genesis.
Source: authors.

dimension reduction of the ordinal dataset. This section elaborates on the methodology adopted for the study.

4.1. Survey design

In 1049 CE, after the Kushwaha clan from Amer won over Nikumbh Yadav, Alapur city was formed (later known as Ulwar), and in 1492 CE, Alawal Khan established a grand city wall boundary around the existing Bala fort. There is a strong influence of the Muslim League on the architecture of the city from 1555 to 1574 CE. The traditional walled city was laid by the 1st Maha Rao Raja Sri Sawai Pratap Singh in 1775 CE with five entry/exit gates: Malakhera gate, Delhi gate, Lal gate, Hajuri gate, and Mahal-chowk gate (Dhingra & Chattopadhyay, 2016; Dhingra et al., 2017). Interactive modes of the interview were transcribed and de-coded to investigate the city's historical genesis, old and existing social setting, its old planning system, and perceptions of local people. The phase-wise evolution of the city is graphically represented in Figs. 3 and 4.

Pilot testing was conducted to differentiate between the contiguous settlements in the city core. Fifty-two samples were randomly surveyed grouped by their survey location: old, intermediate, and new. Kruskal-Wallis test, median test for k-samples, and Jonckheere-Terpstra test rejected the null hypothesis that the median of all sub-groups are equal and suggested significant differences between the characteristics of contiguous neighborhoods. Fig. 5 represents the process adopted for delineation of survey area for conducting final household surveys.

Overall, seventy mohallas under six administrative wards covering approximately 132 ha were identified. Cochran's sample size formula

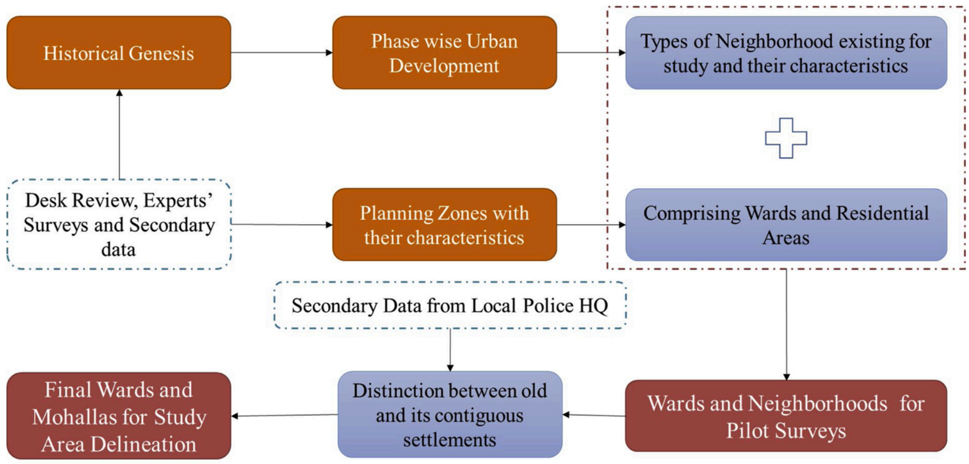


Fig. 5. Delineation of the study area.
Source: authors.

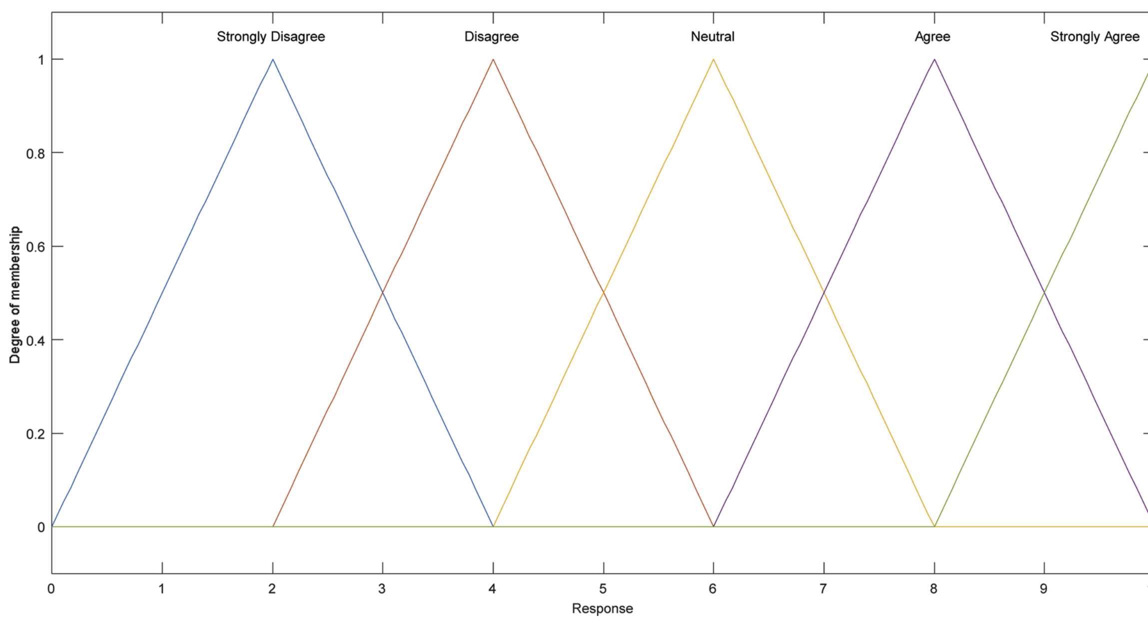


Fig. 6. Fuzzy Rating Scores for Likert scale.
Source: authors.

given by Eqs. (4) and (5) is used to calculate the ideal sample size with 5 % plus-minus precision, 95 % confidence level, and 50 % chances of the estimated proportion of the attribute present in the population. The adjusted sample size is calculated to be 361, but 433 samples were collected to account for missing and incomplete responses, out of which 407 samples were retained for further analysis.

$$n_0 = \frac{Z^2 pq}{e^2} \tag{4}$$

$$n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}} \tag{5}$$

where:

e is the desired level of precision

p is the (estimated) proportion of the population that has the attribute in question, and *q* is *(1 – p)*

n_0 is Cochran's sample size recommendation, *N* is the population size, and *n* is the adjusted sample size.

4.2. Fuzzy arithmetic techniques

Chien and Tsai (2000) measured perceived service quality based on the concept of TFNs with the help of a questionnaire instrument called

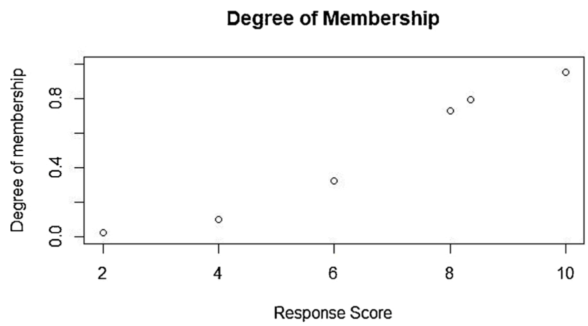


Fig. 7. Linear Membership Function for PCA.
Source: authors.

SERVQUAL. They replaced perceptions of customers by satisfaction degree and expectations by importance degree. They created a TFN for the i^{th} customer's linguistic term using the triplets (0, 0, 2), (0, 2, 4), (2, 4, 6), (4, 6, 8), and (6, 8, 8) of $\widetilde{A}_i$ for $i = 1, 2, 3,\ldots, n$ in linguistic terms, meaning very unimportant, unimportant, fair, important, and very important, respectively. Similarly, the triplets (0, 0, 2), (0, 2, 4), (2, 4, 6), (4, 6, 8), and (6, 8, 8) of $\widetilde{V}_i$ for $i = 1, 2, 3,\ldots, n$ represent very unsatisfied, unsatisfied, fair, satisfied, and very satisfied, respectively. Later the TFNs are aggregated using the averaging operator, and the distance between them provided the difference between the expected and current service quality attributes.

Rattanalertnusorn et al. (2013) also constructed fuzzy rating scores on 5-points Likert scale for which each statement item was assigned values corresponding to responses: *strongly disagree* $(\widetilde{R}_1)$, *disagree* $(\widetilde{R}_2)$, *neither agree nor disagree* $(\widetilde{R}_3)$, *agree* $(\widetilde{R}_4)$ *and strongly agree* $(\widetilde{R}_5)$. They assumed symmetric TFNs: $\widetilde{R}_1, \widetilde{R}_2, \widetilde{R}_3, \widetilde{R}_4$ *and* $\widetilde{R}_5$ represented as *(0,1,2), (1,2,3), (2,3,4), (3,4,5) and (4,5,5)* respectively. Lalla, Ferrari, and Pirotti (2014) denoted i as an index of the interviewed subject and j as an index denoting a concept, and k as a statement or item about the j^{th} concept. Each item, k, has a Likert scale with M_k modalities. The answer of the i^{th} respondent gives an outcome x_{ijk} in *(1; 2; 3; 4[; 5; 6; 7])* depending on the number of modalities. The mean(x_{ij}) of the K_j natural numbers yields a measure of the intensity of the j^{th} concept.

Based on the various approaches adopted by scholars to deal with the imprecision of Likert scale responses, the following steps are applied for the analysis:-

Step 1:- Preparation of survey questionnaires as fuzzy propositions

Let i be an index denoting the interviewed respondent ranging from *1* to n, j be an index denoting the identified indicator or concept to be measured ranging from *1* to m, and k be the linguistic variable of interest about the j^{th} concept ranging from *1* to l. The j^{th} concept is measured through l number of survey statement items semantically connected to it. Most of the k^{th} items have five modalities of the Likert scale denoting the agreement levels of the respondents for each statement, while the rest are interval scale data. The term set of each linguistic variable is assumed vague and imprecise, denoted as fuzzy ratings. For instance, *Strongly Disagree* $(\widetilde{R}_1)$, *Disagree* $(\widetilde{R}_2)$, *Neither Agree Nor Disagree* $(\widetilde{R}_3)$, *Agree* $(\widetilde{R}_4)$ *and Strongly Agree* $(\widetilde{R}_5)$ for Likert scale data as given in Appendix A. TFN is used as an agreement rating score $\widetilde{R}_j$ expressed by Eq. (1).

Step 2:- Data Collection

For this study, the answer of the i^{th} respondent corresponding to j^{th} indicator and k^{th} variable gives an outcome $\widetilde{R}_j$, in the range of {2, 4, 6, 8, 10}. Assuming symmetric TFNs, the answer of the i^{th} household is translated as fuzzy rating scores $\widetilde{R}_1, \widetilde{R}_2, \widetilde{R}_3, \widetilde{R}_4$ *and* $\widetilde{R}_5$ represented by a triplet *(0,2,4),(2,4,6), (4,6,8),* (6,8,10) *and* (8,10,10) respectively (Fig. 6). Besides household surveys, an online survey of experts in the planning domain was conducted on www.qualtrics.com, and the importance of all the indicators was rated on a five-point Likert scale. The average ratings for each indicator, results into a weighting vector defined for m indicators $\forall\ [j] = \{1,2,..,m\}$.

Step 3:- Aggregation Operations on TFNs

The arithmetic mean is the most common method to establish cluster centers for the data (Niskanen, 2004). Arithmetic Averaging (AA) on k linguistic variables assumed equal importance of all the items, given by Eq. (6). The aggregated score of k^{th} variables results in a generalized mean score for its corresponding j^{th} indicator. Further, these fuzzy indicator scores are aggregated using FWA operator to result in SUA fuzzy score using Eq. (3).

$$AA\left(\widetilde{k}_1, \widetilde{k}_2, \ldots, \widetilde{k}_l\right) = \frac{\sum_{k=1}^{l} \widetilde{x_k}}{l} \tag{6}$$

Step 4:- Defuzzification

Chou et al. (2011) and Chen and Hsieh (1997) proposed the Graded Mean Integration Representation (GMIR) method for the representation and ranking of a fuzzy number, based on the integral value of graded mean *h-level* of a fuzzy number. GMIR for TFN *(a, b, c)* is given by Eq. (7).

$$v_{\widetilde{A}} = \frac{a + 4b + c}{6} \tag{7}$$

4.3. Data reduction

Emmenegger et al. (2014) coded respondents who strongly agree with the statement as fully in the set while respondents who somewhat agree are assigned to the membership value 0.8, reflecting the ambiguity in the formulation 'somewhat'. We assume Agreement Fuzzy Set $\widetilde{A}$ with an open right or linear membership function, which gives full membership to responses corresponding to 'Strongly Agree' responses. Membership values for responses with a relatively low agreement to a statement item are assigned a lower degree of membership to fuzzy set $\widetilde{A}$ (Fig. 7).

QCA package in R 3.5.1 is used for fuzzification of ordinal values and mapped into the unit interval with the help of an empirical cumulative distribution function (Thiem & Dusßa, 2013). The threshold for full set exclusion τ_{ex} is 3 (representing the agreement between agreeing and neutral responses), the threshold for the set crossover τ_{cr} is 7 (representing those who are near the neutral responses), and the threshold for full set inclusion τ_{in} is 10 (representing strong agreement). The Fuzzy Coded Dataset (FCD) is calibrated by weighing the original scores with their respective membership values (Alkan & Ganik, 2017).

R Packages CPCA gives results for the standard linear PCA method, while CATPCA and ROBPCA are used for applying NLPCA and RPCA, respectively. ROBPCA algorithm given by Hubert, Rousseeuw, and

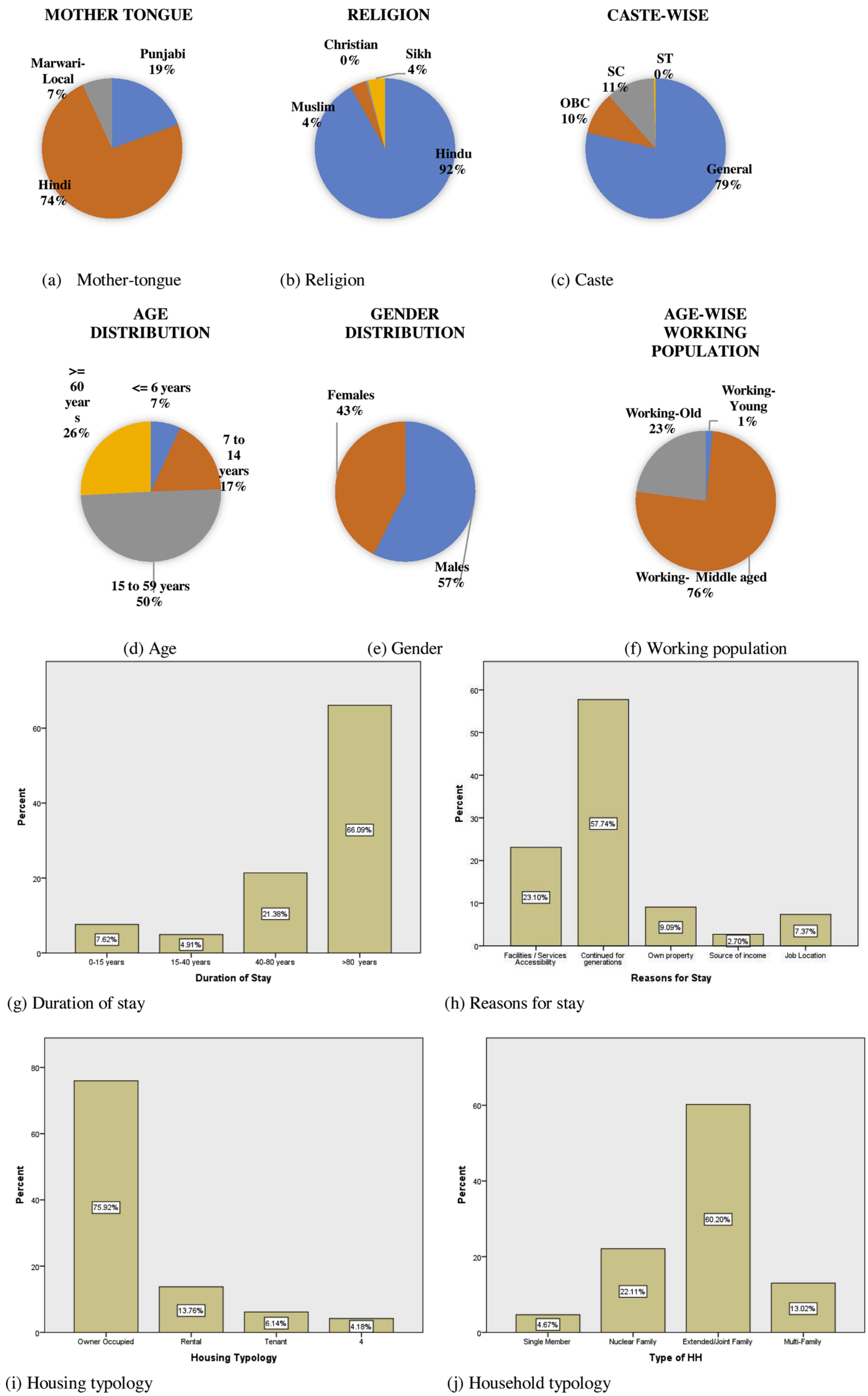
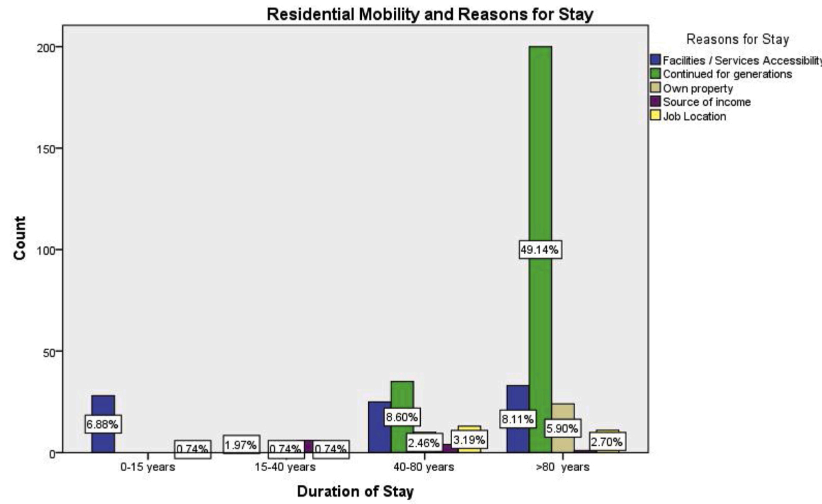
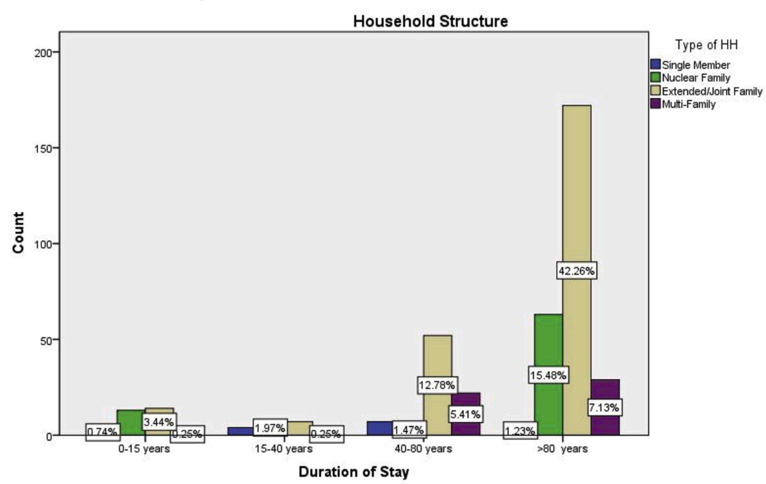


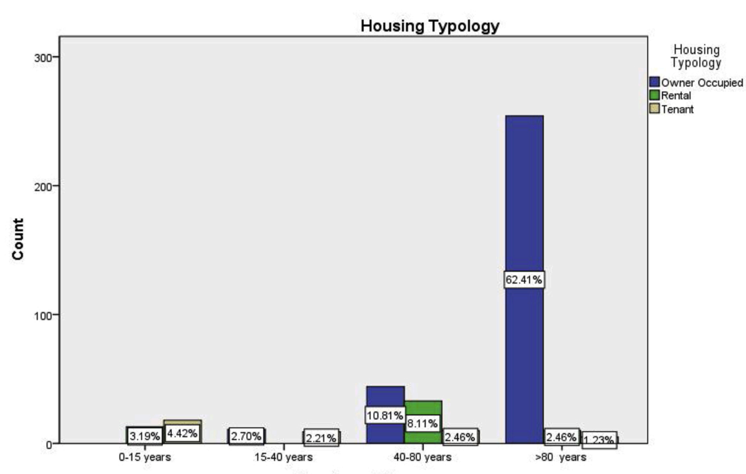
Fig. 8. Respondents' characteristics.
Source: authors.



(a) Reasons for stay

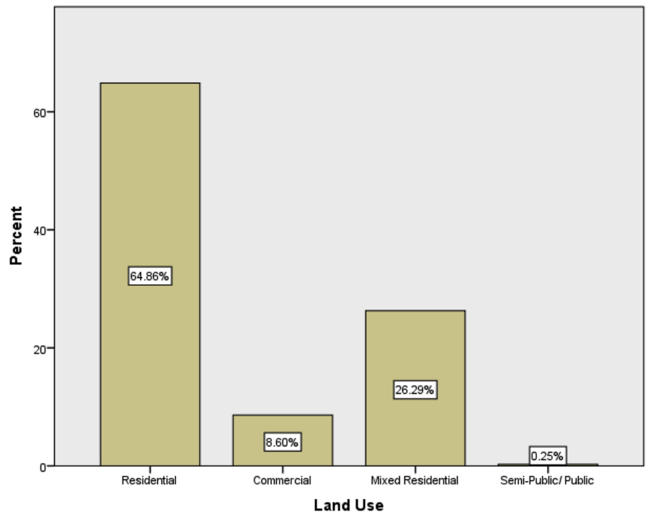


(b) Household structure

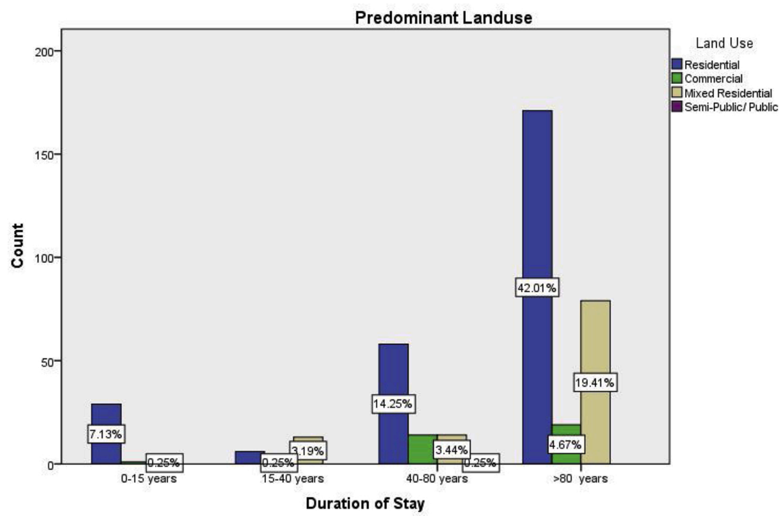


(c) Housing typology

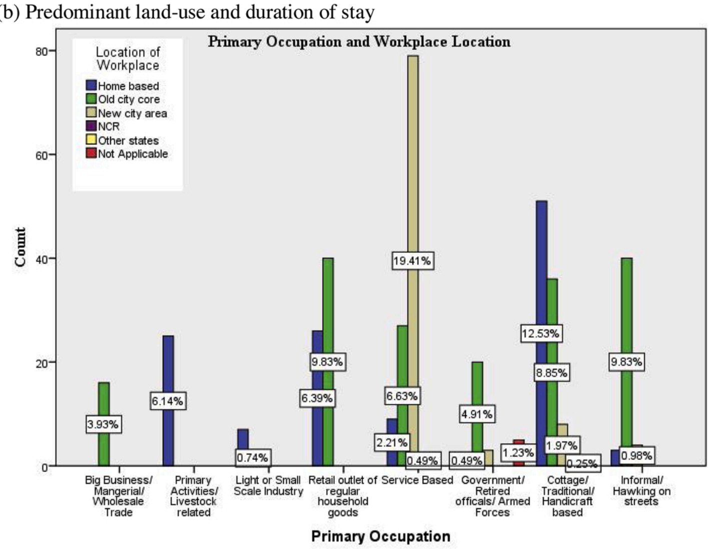
Fig. 9. Residential Mobility.
Source: authors.



(a) Land-use distribution



(b) Predominant land-use and duration of stay



(c) Primary occupation and location

Fig. 10. Land-use.

Table 2
Aggregated Perceptions of the Households.

Smart Urban Attribute		Indicator		Variable		Aggregated Households' Perceptions for kth variable	Aggregated Indicator scores for jth concept	Defuzzified scores for jth concept	Expert's assigned weightages (defuzzified values)	Fuzzy Weighted Average SUA scores	Defuzzified scores for each SUA
		I01	**Comfortable Temperature**	V1	I feel comfortable without AC or desert coolers during summers	(6,36, 8.36, 9.28)	(6.56, 8.56, 9.50)	8.38	3.71		
				V2	I feel comfortable inside the house during winters	(6.75, 8.75, 9.71)					
		I02	**Level of Noise**	V3	There is no disturbance by high decibels of noise from traffic/ industries/streets/community events	(7.09, 9.09, 9.99)	(7.09, 9.09, 9.99)	8.90	3.72		
SUA 1	**Local Environmental Quality**	**I03**	**Local Pollution**	V4	We haven't observed any air borne or water borne diseases in our mohalla in the recent years	(6.39, 8.39, 9.43)	(5.33, 7.33, 8.45)	7.19	3.86	(6.31, 8.31, 9.30)	8.14
				V5	Heavy traffic/traffic congestion/high speed traffic/ pollution caused by vehicles are no problem	(7.13, 9.13, 9.78)					
				V6	Ratio of Bicycles to Total Vehicles owned	(2.48, 4.48, 6.14)					
				V7	I feel safe during day on streets around our house.	(7.51, 9.51, 9.96)					
				V8	I feel safe after sunset on streets around our house	(7.37, 9.37, 9.92)					
				V9	I feel safe during day while crossing streets around our house.	(7.50, 9.50, 9.96)					
				V10	I feel safe after sunset while crossing streets around our house.	(7.49, 9.49, 9.94)					
		I04	**Residents perception about safety in the neighborhood**	V11	I feel safe during day around chowks and public spaces such as religious buildings	(7.48, 9.48, 9.93)	(7.27, 9.27, 9.89)	9.04	3.92		
SUA 2	**Sense of Safety and Security**			V12	I feel safe after sunset around chowks and public spaces such as religious buildings	(7.15, 9.15, 9.90)				(7.14, 9.14, 9.84)	8.93
				V13	I feel safe during day around vacant properties	(7.11, 9.11, 9.83)					
				V14	I feel safe after sunset around vacant properties	(7.16, 9.16. 9.79)					
				V15	I feel safe during day in parks around our house.	(6.78, 8.78, 9.85)					
				V16	I feel safe after sunset in parks around our house.	(7.10, 9.10, 9.81)					
				V17	Till what time in night, do you find people of streets?	(6.17, 8.17, 9.58)					
				V18	The local streets are well lit	(6.83, 8.83, 9.62)					
		I05	**Eyes on streets**	V19	Walkers/bikers on the streets can be seen from our home	(7.54, 9.54, 10.00)	(7.01, 9.01, 9.79)	8.81	3.63		
				V20	We can See and speak to others when walking in mohalla	(7.50, 9.50, 9.97)					
SUA 3		**I06**	**Performance of basic services**	V21	We are quite satisfied with the performance of ULBs	(4.72, 6.72, 8.19)	(4.61, 6.61, 8.10)	6.53	4.53	(5.32, 7.19, 8.15)	7.04

(*continued on next page*)

Table 2 (*continued*)

Smart Urban Attribute		Indicator		Variable		Aggregated Households' Perceptions for kth variable	Aggregated Indicator scores for jth concept	Defuzzified scores for jth concept	Expert's assigned weightages (defuzzified values)	Fuzzy Weighted Average SUA scores	Defuzzified scores for each SUA
				V22	Our ULB is quite effective in managing urban services such as drainage, sewerage, water supply	(4.15, 6.51, 8.01)					
				V23	Our mohalla is attractive in terms of its natural sights, building facades/unique space qualities.	(6.20, 8.20, 9.15)					
	Perceived Residential Environment	**I07**	**Quality of Urban Spaces**	V24	The streets are quite clean and beautiful	(7.97, 9.97, 9.98)	(6.08, 8.08, 8.86)	7.87	4.18		
				V25	The new development in our mohalla is in coordination with existing buildings	(4.05, 6.05, 7.44)					
				V26	It is comfortable to walk or cycle on the streets	(7.54, 9.54, 9.82)					
		I08	**Connectivity or Walkable destinations**	V27	Who prefers mostly to walk in your household?	(6.59, 8.59, 9.13)	(5.34, 6.94, 7.47)	6.76	4.09		
				V28	Conveyance Choice to School	(5.34, 7.34, 8.66)					
				V29	Conveyance Choice to Market	(7.20, 9.20, 9.73)					
		I09	**Resident Mobility Rate**	V30	Duration of Stay	(6.67, 8.67, 9.35)	(6.67, 8.67, 9.35)	8.45	3.56		
		I10	**Degree of Tolerance**	V31	People around here are willing to help and share with their neighbors	(7.32, 9.32, 9.76)	(7.36, 9.36, 9.81)	9.10	3.47		
				V32	There is no communal bias or segregation in our mohalla	(7.40, 9.40, 9.85)					
				V33	We often visit/chat with our neighbors on streets/chowks/ religious places	(6.36, 8.83, 9.10)					
SUA 4	**Collective Efficacy and Social Cohesion**	**I11**	**Incidences of Social Interaction**	V34	I know 7–10 immediate neighbors quite well	(6.84, 8.84, 9.74)	(6.49, 8.83, 9.36)	8.53	3.90	(6.83, 8.92, 9.52)	8.67
				V35	The level of interaction between young and elderly is significantly high in our mohalla	(6.28, 8.81, 9.24)					
		I12	**Degree of interpersonal trust**	V36	In this mohalla, when someone is not at home, their neighbours will watch over their property	(7.10, 9.10, 9.84)	(6.86, 8.86, 9.60)	8.65	3.88		
				V37	We often discuss and ask each other advice about personal matters such as jobs and family	(6.61, 8.61, 9.36)					
		I13	**Cultural Freedom**	V38	We feel safe to follow our lifestyle and cultural practices	(7.37, 9.37, 9.86)	(7.25, 9.25, 9.71)	8.99	3.87		
SUA 5	**Cultural Vitality**			V39	We attend community functions quite often in our mohalla and have strong social ties with our neighbors during festivals and fairs	(7.13, 9.13, 9.57)				(5.79, 7.79, 8.64)	7.60
		I14	**Sense of Belongingness**	V40	We feel a strong sense of belongingness to our mohalla	(6.84, 8.84, 9.47)	(6.84, 8.84, 9.47)	8.61	4.15		
		I15	**Heritage Value**	V41	Intangible Cultural Significance	(1.77, 3.77, 5.33)	(2.54, 4.54, 6.14)	4.47	3.06		
				V42	Significance of the neighborhoods	(4.15, 6.15, 7.84)					

(*continued on next page*)

Table 2 (*continued*)

Smart Urban Attribute	Indicator		Variable		Aggregated Households' Perceptions for kth variable	Aggregated Indicator scores for jth concept	Defuzzified scores for jth concept	Expert's assigned weightages (defuzzified values)	Fuzzy Weighted Average SUA scores	Defuzzified scores for each SUA
			V43	Buildings of Historical Importance	(1.69, 3.69, 5.27)					
SUA 6 **Economic Contribution**	**I16**	**Workplace Characteristics**	V44	Primary Occupation	(4.75, 6.75, 8.52)	(4.41, 6.41, 7.96)	6.34	3.84	(2.68, 4.68, 6.45)	4.64
			V45	Land Use	(2.45, 4.45, 5.92)					
			V46	Workplace Location	(6.03, 8.03, 9.43)					
	I17	**Workforce Characteristics**	V47	Ratio of female to male workers	(1.03, 3.03,5.03)	(0.90, 2.90, 4.90)	2.90	3.74		
			V48	Ratio of youth to total workers	(0.07, 2.07, 4.07)					
			V49	Ratio of old to total workers	(1.59, 3.59, 5.59)					

Branden (2005), combines both Projection Pursuit (PP) and Robust Covariance Estimation method for the high dimensional dataset. The PP part is used for the initial dimension reduction, further on which Minimum Covariance Determinant (MCD) estimator is applied. rrcov and gifi packages are used in R software version 3.5.1.

5. Results and discussion

5.1. Respondents' characteristics

The dataset for the given analysis consists of 49 variables and 17 indicators. The micro-level data collected as Likert and interval scale is transformed to an ordinal scale for data analysis with the highest rating assigned to the most preferred choices. The household survey shows the majority of respondents as Hindi speaking (74 %) followed by Marwari (19 %) and Punjabi (7 %) languages (Fig. 8(a)). Around 79 % belong to the general category, with 11 % scheduled caste and 10 % other backward classes (Fig. 8(c)). The study area is Hindus dominated, comprising 92 % of households, and the rest belong to Sikhs and Muslims (Fig. 8(b)).

Fig. 8(d) shows that around 50 % of households are in the age group 15–59 years, followed by 26 % above 60 years and 24 % less than 14 years of age. There are 57 % males, and 43 % females (Fig. 8(e)), and around 76 % working population is middle-aged followed by 23 % old population and 1 % young population (Fig. 8(f)). Most of the households are living for more than 80 years now (66 %), followed by those who are staying for 40–80 years (21.38 %), 15–40 years (4.91 %), and less than 15 years (7.62 %) as shown in Fig. 8(g). Figs. 8(h) and 9 (a) show that around 57.74 % of households mentioned their reasons for stay as their continuity for generations, indicating a strong sense of belongingness. Others gave equal weightage to accessibility to facilities/services, ownership of a property, having them as a source of income, and location of the workplace.

Around 76 % of households are owner-occupied, out of which 62.42 % have stayed for generations (Fig. 8(i)). Relatively new residents and refugees who settled post-partition of India are tenants (4.42 %) and own rental housing (8 %), respectively, as shown in Fig. 9(c). The existing family structure shows that around 60 % of households have extended or joint families followed by 22 % of nuclear families (Fig. 8 (j)). Most of these joint families (42.26 %) belong to those who settled for more than 80 years and carry forward their families' heritage even today, while around 13 % have a multi-family structure with many families of different clans staying together (Fig. 9(b)).

The land use analysis shows that around 65 % of households are residential, followed by approximately 27 % mixed residential with local economic activities running from their homes either as cottage industries or as local convenience shops (Fig. 10(a)). The older generations still maintain residential activities (~42 %) followed by mixed residential (~19 %) (Fig. 10(b)). The primary occupation of the households is service-based (~29 %), followed by cottage and home-based small scale industries (~24 %) (Fig. 10(b)). Around 45 % of households work in the old city core within walkable distances, and around 30 % have home-based enterprises, while 19 % of service-based households commute daily to the extended city areas for work (Fig. 10 (c)).

5.2. Fuzzy aggregation operation

Three levels of abstraction are identified for the hierarchical evaluation of households' responses. In the first and second levels, the variables and indicators are aggregated using the AA operator to give TFN score. The third level of assessment applies experts' weightages for each indicator and calculates an aggregated TFN for SUA using the FWA operator. In order to demonstrate the calculations undertaken for the analysis, let us take an example of the *SUA 2: Sense of Safety and Security, which* comprises of two indicators viz *I04: Residents perception*

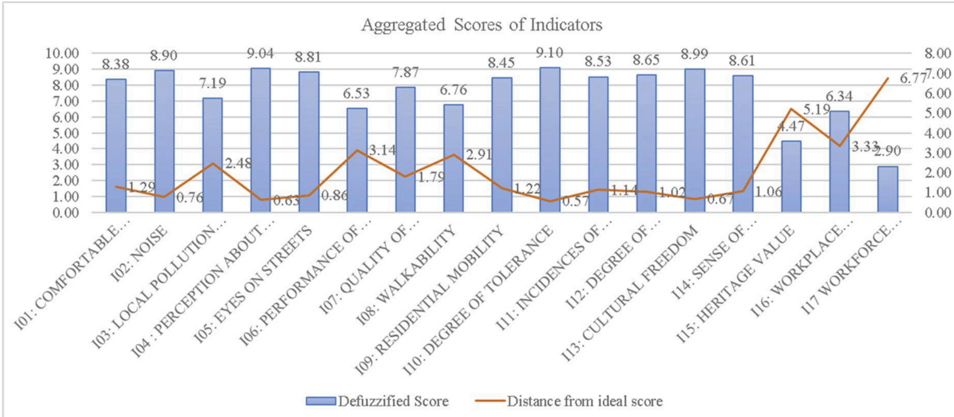


Fig. 11. Aggregated Scores of indicators.
Source: authors.

about safety in the neighborhood and *I05: Eyes on streets*. *I04* consists of ten variables as survey items *(V7 to V 16),* and similarly, *I05* consists of four variables as survey items *(V17 to V20)* as shown in Table 2. This SUA captures the local residents' perceptions about the sense of safety in their neighborhood. The responses were collected on a Likert scale with five modalities: *strongly disagree, disagree, neutral, agree, and strongly agree*. These responses for each i^{th} household are converted to TFNs following the methodology discussed earlier.

Let the responses of the first and second household for V7 ($i = 1$; $i = 2$; $k = 7$) as TFN_1 *(8, 10, 10)* and TFN_2 *(4, 6, 8)* respectively, i.e., the first respondent strongly agrees, and the second respondent is neutral or undecided about the statement corresponding to variable *V7*. Their aggregated mean score can be given by $TFN\left(\frac{8+4}{2}, \frac{10+6}{2}, \frac{10+8}{2}\right) = TFN\ (6, 8, 9)$. In a similar manner, we have calculated aggregated scores for each j^{th} indicator by applying AA operator on comprising k variables (in this case, for $j = 4$, $k = 7$–16 are aggregated).

Further, indicators *I04* and *I05* are aggregated using FWA operator to derive aggregated score of *SUA2*. The corresponding average TFNs for weightages of *I04* and *I05* are calculated as *(3.30, 3.97, 4.30)* and *(3.09, 3.65, 4.09)*, respectively. These TFNs are defuzzified using GMIR method: $w_{I04} = \frac{3.30+(4\times 3.97)+4.30}{6}$ and $w_{I05} = \frac{3.09+(4\times 3.65)+4.09}{6}$ resulting in *3.92* and *3.63* as their crisp weightages. The average TFN for *I04* and *I05* with respect to all the *407* respondents and comprising variables are calculated as TFN_{I04}*(7.96, 9.27. 9.89)* and TFN_{I05} (7.62, 9.01, 9.79), respectively. The FWA score of *SUA 2* is thus calculated as $TFN_{SUA2}\left(\frac{(3.92\times 7.96)+(3.63\times 7.62)}{(3.92+3.63)}, \frac{(3.92\times 9.27)+(3.63\times 9.01)}{(3.92+3.63)}, \frac{(3.92\times 9.89)+(3.63\times 9.79)}{(3.92+3.63)}\right) = TFN_{SUA2}(7.80, 9.14, 9.84)$.

The defuzzified score of *SUA2* is given by $\left(\frac{7.80+(4\times 9.14)+9.84}{6}\right) =$ *9.03*, which can be further used for finding the distance from the ideal score. Since the ideal score for each response is TFN_{ideal}*(8, 10, 10)*, which can also be written as a crisp value of *9.67*. The difference of the ideal score and the actual score of *SUA2* gives the distance between them, i.e. *(9.67 – 9.03) =0.64*. Table 2 summarises the results of fuzzy arithmetic operations carried out to calculate aggregated perceptions of the households.

Fig. 11 shows that degree of tolerance, residents' perception about safety and sense of cultural freedom rank highest while workforce

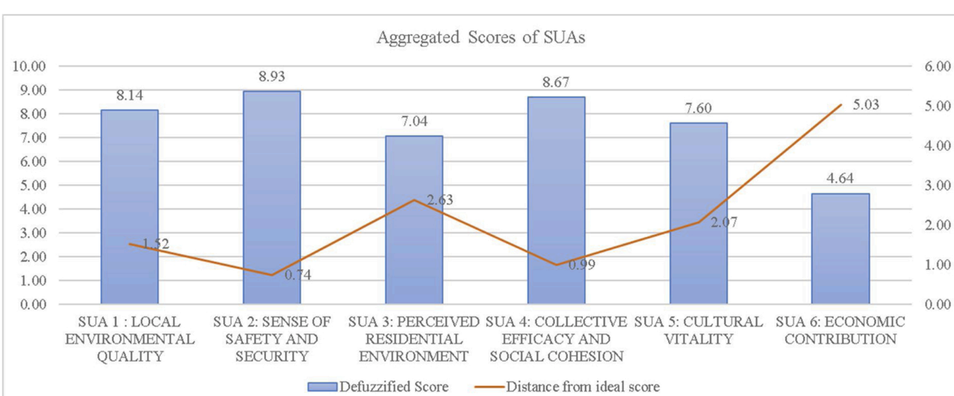
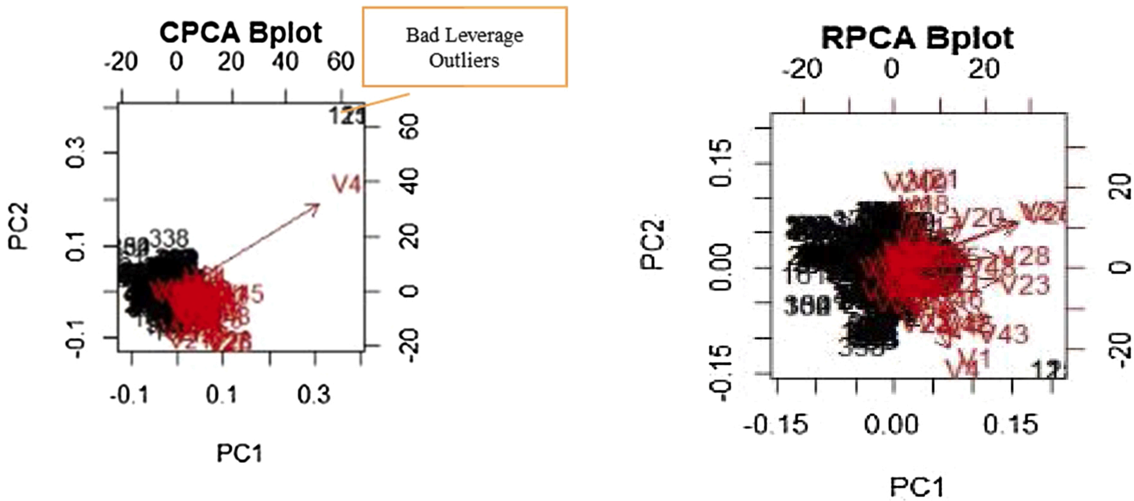
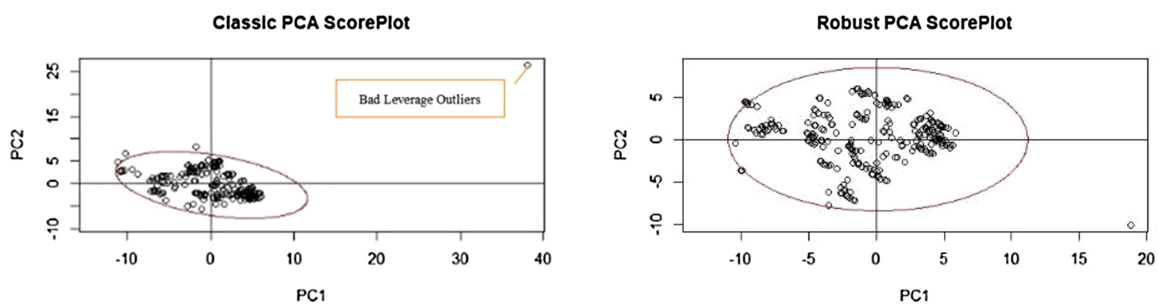


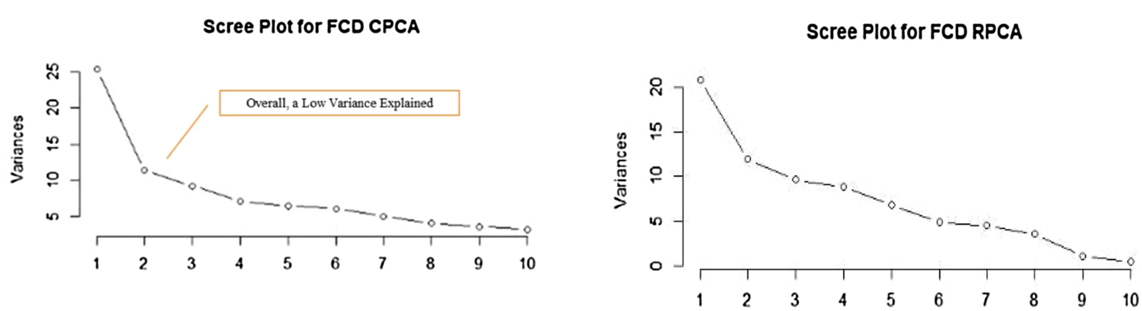
Fig. 12. Aggregated Scores of SUAs.
Source: authors.



a) Bipolar-plot

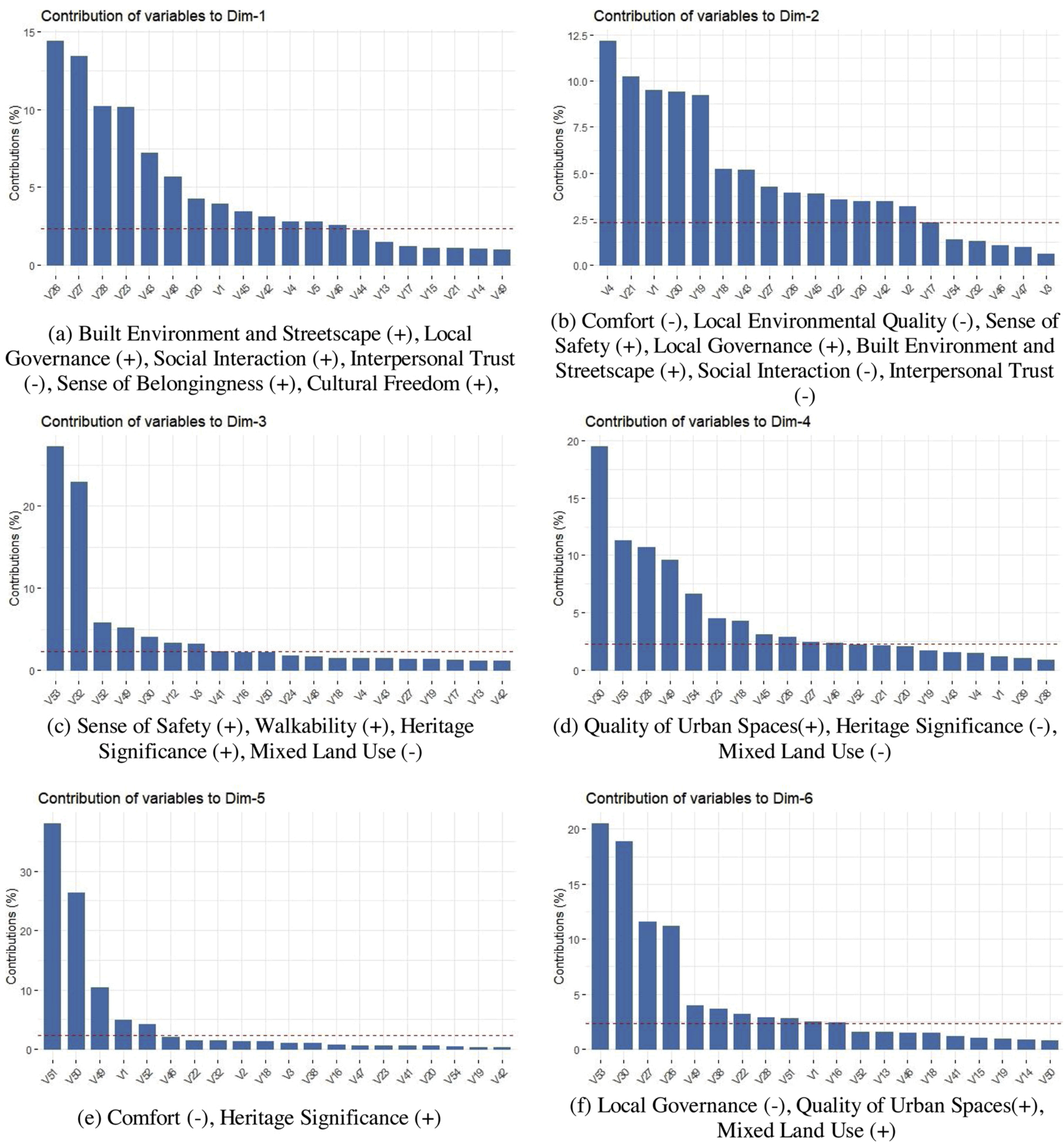


b) Score-plot



c) Scree-Plot

Fig. 13. Comparative Plots for comparison of CPCA and RPCA.



(a) Built Environment and Streetscape (+), Local Governance (+), Social Interaction (+), Interpersonal Trust (-), Sense of Belongingness (+), Cultural Freedom (+),

(b) Comfort (-), Local Environmental Quality (-), Sense of Safety (+), Local Governance (+), Built Environment and Streetscape (+), Social Interaction (-), Interpersonal Trust (-)

(c) Sense of Safety (+), Walkability (+), Heritage Significance (+), Mixed Land Use (-)

(d) Quality of Urban Spaces(+), Heritage Significance (-), Mixed Land Use (-)

(e) Comfort (-), Heritage Significance (+)

(f) Local Governance (-), Quality of Urban Spaces(+), Mixed Land Use (+)

Fig. 14. Principal Components Extracted (87.94 % VAF).

characteristics and heritage significance didn't perform so well. This can be attributed to the weak nature of these variables due to the subjective fuzzification of numerical values. Fig. 12 shows that the sense of safety and security amongst the residents performs best, closely followed by collective efficacy, social cohesion, and local environmental quality.

5.3. Data reduction

Fundamentally, the new variables should be able to preserve the best possible variability and should be uncorrelated with each other (Jollife & Cadima, 2016). We understand that those dimensions, which nearly explain 80 % of the total variance in social surveys, may give a better picture of the whole dataset. Application of CPCA on FCD explains 30.92 % of the variance by the first PC, and the first six PCs explain more than 80 % of the total variance. Application of RPCA on FCD explains 28.41 % of the variance by the first PC, and first five PCs explain more than 80 % variance. However, CATPCA on FCD explains 24.44 % variance by the first PC, and more than ten PCs are required to explain more than 80 % variance.

This shows the ineffectiveness of CATPCA to reduce an ordinal dataset as it is unable to explain enough variance. CPCA is also found to be ineffective owing to its high sensitivity to the presence of outliers. RPCA produces considerably better coverage of the dataset irrespective of outliers (Fig. 13(a) and (b)). Fig. 13(c) shows that though CPCA explains maximum variance by the first PC, the PCs produced from RPCA overall explain more variance than CPCA.

RPCA on FCD resulted in six dimensions, which accounts for a total variance of 87.94 %. The contributions of variables to each of these dimensions are illustrated in Fig. 14. Dimension 1 corresponds positively to the built environment and streetscape, local governance, social interaction, sense of belongingness, and cultural freedom and negatively to the interpersonal trust (Fig. 14(a)). Dimension 2 corresponds positively to the built environment and streetscape, local governance, and sense of safety and negatively to comfort-level, local environmental quality, social interaction, and interpersonal trust (Fig. 14(b)).

Dimension 3 corresponds positively to the sense of safety, walkability, and heritage significance and negatively to mixed land use (Fig. 14(c)). Dimension 4 corresponds positively to the quality of urban spaces and negatively to heritage significance and mixed land use (Fig. 14(d)). Dimension 5 corresponds positively to heritage significance and negatively to comfort-level (Fig. 14(e)). Dimension 6 corresponds positively to the quality of urban spaces and mixed land use and negatively to local governance (Fig. 14(f)).

6. Conclusion

Vagueness is an inherent feature and a type of epistemic uncertainty, which is inescapable in all theoretical and empirical analyses of social, behavioral, and political phenomena (Arfi, 2013; Bandemer & Naether, 1992; Klir & Yuan, 1932). Smartness is also an ambiguous concept that has different meanings to different people at different times and places. Comprehensive literature review and computation based text analysis identify the objectives of smart urban development. Based on this, the authors have identified a relevant set of indicators for the assessment of socio-cultural attributes at the neighborhood-level in an HUL. The study emphasizes that a real smart city should integrate the complex ecosystems of people, their institutions, and heritage in the entire process, and their underlying potential should be realized beyond tourism.

Since the data collection is not feasible at the micro-level for Indian cities, household surveys were conducted to gather qualitative information from its residents. The dataset for the given analysis consists of 43 linguistic variables and 17 indicators. Household surveys were conducted in the historic city of Alwar to capture the perceptions of its old inhabitants about their residential environment in terms of socio-cultural concepts such as a sense of safety, belongingness, and interpersonal trust. Overall, seventy traditional neighborhoods under six administrative wards were delineated based on secondary data analysis and pilot surveys.

These collective attitudes and perceptions can quantify the latent traits of a society (Prokop & Řezanková, 2011; Vonglao, 2017). However, high precision is incompatible with the high complexity associated with a humanistic system, and thus, linguistic variables are preferred to their numerical counterparts (Zadeh, 1975). Such human linguistic concepts are naturally vague; hence fuzzy logic is not only beneficial but also necessary in real-world settings (McNeill & Thro, 1994; Niskanen, 2004; Smithson, 1983). Fuzzy linguistic variables can capture the qualitative differences in a way that classical indicators cannot while computing with imprecise and uncertain values (Emmenegger et al., 2014; Hassall, 1999; Rattanalertnusorn et al., 2013)

The Likert and interval scale data are transformed to an ordinal scale to maintain homogeneity. Fuzzy arithmetic and weighted averaging operators result in aggregated scores for all the variables, indicators, and SUAs. For dimension reduction, the study assumes the responses collected as fuzzy propositions with a linear membership function. The original dataset is weighed using the derived degree of membership values to give FCD. The results obtained from the application of RPCA on FCD gave better results, taking care of outliers and uncertainty in the dataset.

The study concludes better performance of socio-cultural attributes of HUL, indicating the inherent smart features of an existing community. It is imperative to capitalize on the existing social and cultural capital of old cities worldwide, rather than merely fixing the spatial setting with technology. The major disadvantage of fuzzy logic is the challenge of justifying the membership function of respondents' perceptions and expectations (Chou et al., 2011). Due to limitations of the scope of the study, authors recommend future research to use allied Fuzzy Multi-Criteria Decision Making (FMCDM) techniques such as fuzzy AHP for calculating weightages and ranking of the indicators. Future researchers should also consider a hybrid fuzzy logic approach, which uses both subjective and objective datasets.

Declaration of Competing Interest

The authors report no declarations of interest.

Acknowledgments

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Appendix A

Survey no.

Annexure 1

LOCAL RESIDENTS' SURVEY, Alwar, Rajasthan

Conducted by: Mani Dhingra, in partial fulfillment of Doctor of Philosophy degree (PhD)

Supervisor- Dr. Subrata Chattopadhyay

Department of Architecture and Regional Planning, IIT Kharagpur

A. BACKGROUND INFORMATION OF HOUSEHOLD

A1 Mohalla Name								
A2 Primary Occupation	Big business/ Managerial/ Wholesale – Trade [1]	Primary Activities / Livestock related [2]	Light or Small scale industries [3]	Retail outlet of regular household goods [4]	Service based [5]	Government / Retired Officials/ Armed forces etc [6]	Cottage/ Traditional/ Handicrafts based [7]	Informal job/Hawkers etc [8]

A3 Location	Home Based [1]	Old city core [2]	New City Area [3]	NCR [4]	Other states [5]	**A4 Working Members**	A4.1 Males	A4.2 Females	A4.3 Young[1]	A4.4 Middle age[2]	A4.5 Old

A5 Mothe Tongue	Punjabi [1]	Hindi [2]	Marwari [3]	Others [99]	
A6 Religi	Hindu [1]	Muslim [2]	Christian [3]	Sikh [4]	Others [99]
A7 Caste	General [1]	OBC [2]	SC [3]	ST [4]	

A8 Duration of Stay	0-15 years [1]	15 to 40 years [2]	40 to 80 years [3]	> 80 years [4]
A9 Reasons for stay	Facilities / Services Accessibility [1]	Continued for generations [2]	Own property [3]	Source of income [4]
A10 Housing Typology	Owner occupied [1]	Rental [2]	Tenant [3]	
A11 Land use	Residential [1]	Commercial [2]	Mixed Residential [3]	Semi Public/ Public [4]
A12 Type of HH	Single Member [1]	Nuclear Family[3] [2]	Extended Family[4] [3]	Multi-family[5] [4]

A13 No. of Families in Dwelling unit		**A14 No. of Family Members**	A14.1 Males	A14.2 Females	A14.3 6 years & below	A14.4 7 – 14 years	A14.5 15 – 59 years	A14.6 60 years & above

A15 Average Monthly Income	Zero:[1], up to Rs.10,000 :[2], Rs.25,000:[3], Rs.50,000:[4], above Rs.50,000:[5]	**A16 Average Monthly Expenditure**	Zero:[1], up to Rs.10,000 :[2], Rs.25,000:[3], Rs.50,000:[4], above Rs.50,000:[5]
A17 Income from cultural activities?			
A18 Monthly Income from the rent	Zero:[1], up to Rs.10,000 :[2], Rs.25,000:[3], Rs.50,000:[4], above Rs.50,000:[5]	**A19 Monthly expenditure on housing (maintenance / rent/ loan repayment/ others)**	Zero:[1], up to Rs.10,000 :[2], Rs.25,000:[3], Rs.50,000:[4], above Rs.50,000:[5]

A20 No of vehicles owned	A20.1 Bicycles		A20.2 2-wheeler		A20.3 4- wheeler	

[1] Youth are defined as those aged 15 to 29 in the national youth policy (2014)
[2] Middle age include those who are between 30 and 60 years and hence, don't fall under old age category which is > 60 years for this survey
[3] family group consisting of two parents and their children (one or more).
[4] family that extends beyond the nuclear family, consisting of parents, aunts, uncles, and cousins, all living nearby or in the same household.
[5] accommodation designed for occupation by more than one family.

A21 Do you own a smartphone or laptop with internet facility?	Yes [1]			No [0]	
A22 Proficiency of using digital services	No knowledge [1]	Beginner [2]		Intermediate [3]	Expert [4]
B. LOCAL PERCEPTIONS & PREFERENCES					
How strongly do you agree with the following statements?					
SUA 1: Local Environmental Quality					
B1 I feel comfortable without AC or desert coolers during summers	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B2 I feel comfortable inside the house during winters	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B3 There is no disturbance by high decibels of noise from traffic/ industries/ streets/ community events	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B4 We haven't observed any air borne or water borne diseases in our mohalla in the recent years	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B5 Heavy traffic/ traffic congestion/ high speed traffic/ pollution caused by vehicles are no problem	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
SUA 2: Sense of Safety and Security					
B6 I feel safe during day on streets around our house.	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B7 I feel safe after sunset on streets around our house	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B8 I feel safe during day while crossing streets around our house.	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B9 I feel safe after sunset while crossing streets around our house.	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B10 I feel safe during day around chowks and public spaces such as religious buildings	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B11 I feel safe after sunset around chowks and public spaces such as religious buildings	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B12 I feel safe during day around vacant properties	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B13 I feel safe after sunset around vacant properties	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B14 I feel safe during day in parks around our house.	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B15 I feel safe after sunset in parks around our house.	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B16 Till what time in night, do you find people of streets?	Late midnight [4]	Around 9 – 10 pm [3]		Around 7 - 8 pm [2]	Deserted [1]
B17 The local streets are well lit	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B18 Walkers/bikers on the streets can be seen from our home	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B19 We can See and speak to others when walking in mohalla	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
SUA 3: Perceived Residential Environment					
B20 We are quite satisfied with the performance of ULBs	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B21 Our ULB is quite effective in managing urban services such as drainage, sewerage, water supply	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B22 Our mohalla is attractive in terms of its natural sights, building facades/ unique space qualities.	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B23 The streets are quite clean and beautiful	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]

B24 The new development in our mohalla is in coordination with existing buildings	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B25 It is comfortable to walk or cycle on the streets	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B26 Who prefers mostly to walk in your household?	Females[1]	Elders[2]	Males[3]	Youth[4]	Everyone [5]
SUA 4: Collective Efficacy and Social Cohesion					
B27 People around here are willing to help and share with their neighbors	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B28 There is no communal bias or segregation in our mohalla	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B29 We often visit / chat with our neighbors on streets/ chowks / religious places	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B30 I know 7 to 10 immediate neighbors quite well	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B31 The level of interaction between young and elderly is significantly high in our mohalla	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B32 In this mohalla, when someone is not at home, their neighbours will watch over their property	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B33 We often discuss and ask each other advice about personal matters such as jobs and family	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
SUA 5: Cultural Vitality					
B34 We feel safe to follow our lifestyle and cultural practices	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B35 We attend community functions quite often in our mohalla and have strong social ties with our neighbors during festivals and fairs	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B36 We feel a strong sense of belongingness to our mohalla	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
Spatial Indicators					
B37 Parking is not a problem	Strongly agree [5]	Agree [4]	Undecided [3]	Disagree [2]	Strongly disagree [1]
B38 Parking location for personal vehicles	Within House [1]	Outside mohalla [2]	On roadside [3]		Dedicated parking location name: [4]

C. ACCESSIBILITY ANALYSIS

Facility / Services	**C1** Approximate Commuting Distance (km) (< 1 km [1], 1 to 3 km [2], 3 to 5 km [3], > 5 km[4])	**C2** Conveyance Choice (walking [1], Cycle [2], 2-wheeler [3], 4-wheeler [4], auto [5], bus [6])
1 School		
2 Market		
3 Taxi/ Auto Stand		
4 Parks		
5 Religious places & CGPs		

References

Albino, V., Berardi, U., & Dangelico, R. M. (2015). Smart cities: Definitions, dimensions, performance, and initiatives. *Journal of Urban Technology, 22*(1), 3–21. https://doi.org/10.1080/10630732.2014.942092

Alkan, B. B., & Ganik, S. (2017). Robust principal component analysis based on fuzzy coded data. *Anadolu University Journal of Science and Technology A- Applied Sciences and Engineering, 18*(3), 754–762. https://doi.org/10.18038/aubtda.317765

Angelidou, M. (2014). Smart city policies: A spatial approach. *Cities, 41*, 3–11. https://doi.org/10.1016/j.cities.2014.06.007

Angelidou, M. (2017). The role of smart city characteristics in the plans of fifteen cities. *Journal of Urban Technology, 24*(4), 3–28. https://doi.org/10.1080/10630732.2017.1348880

Arfi, B. (2013). Linguistic fuzzy logic methods in social sciences. In J. Kacprzyk (Ed.), *Studies in fuzziness and soft computing* (Vol. 253, pp. 1689–1699). Springer. https://doi.org/10.1007/978-3-642-13343-5.

Aurigi, A., & Odendaal, N. (2020). From "Smart in the Box" to "Smart in the city": Rethinking the socially sustainable smart city in context. *Journal of Urban Technology, 0*(0), 1–16. https://doi.org/10.1080/10630732.2019.1704203

Aydin, O., & Pakdil, F. (2008). Fuzzy SERVQUAL analysis in airline services. *Organizacija, 41*(3), 108–115. https://doi.org/10.2478/v10051-008-0012-8

Bandemer, H., & Naether, W. (1992). Fuzzy data analysis. *Theory and declslon library-Serles B: Mathematical and statistical methods.* SPRINGER SCIENCE+BUSINESS MEDIA, B.Y.

Bede, B. (2013). Mathematics of fuzzy sets and fuzzy logic. In J. Kacprzyk (Ed.), *Studies in fuzziness and soft computing.* Springer Verlag. https://doi.org/10.1007/978-3-642-35221-8.

Bednarska-Olejniczak, D., Olejniczak, J., & Svobodová, L. (2019). Towards a smart and sustainable city with the involvement of public participation-The case of Wroclaw. *Sustainability, 11*(2), 1–33. https://doi.org/10.3390/su11020332

Brown, D. (2009). Good practice guidelines for indicator development and reporting. *A contributed paper third world forum on 'Statistics, knowledge and policy' charting progress, building visions, improving life* (Issue October) http://www.oecd.org/site/progresskorea/43586563.pdf.

Burhan Turksen, I., & Willson, I. A. (1994). A fuzzy set preference model for consumer choice. *Fuzzy Sets and Systems, 68*(3), 253–266. https://doi.org/10.1016/0165-0114(94)90182-1

Cabitza, F., & Ciucci, D. (2018). Fuzzification of ordinal classes. The case of the HL7 severity grading. *Lecture notes in computer science (Including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics)* (pp. 64–77). https://doi.org/10.1007/978-3-030-00461-3_5, 11142 LNAI (January).

Carifio, J., & Perla, R. J. (2007). Ten common misunderstandings, misconceptions, persistent myths and urban legends about Likert scales and Likert response formats and their antidotes. *Journal of Social Sciences, 3*(3), 106–116.

Castelnovo, W. (2016). Co-production makes cities smarter: Citizens' participation in smart city initiatives. *E-Participation in smart cities: Technologies and models of governance for citizen engagement* (pp. 97–117). Cham: Springer. https://doi.org/10.1007/978-3-319-30558-5_7

Chen, S.-M. (1996). Evaluating weapon systems using fuzzy arithmetic operations. *Fuzzy Sets and Systems, 77*(3), 265–276. https://doi.org/10.1016/0165-0114(95)00096-8

Chen, S. H., & Hsieh, C. H. (1997). Representation, ranking, distance, and similarity of L-R type fuzzy number and application. *Australian Journal of Intelligent Processing Systems, 6*(4), 217–229.

Chien, C., & Tsai, H. (2000). Using fuzzy numbers to evaluate perceived service quality. *Fuzzy Sets and Systems, 116*, 289–300.

Chou, C., Liu, L., Huang, S., Yih, J., & Han, T. (2011). An evaluation of airline service quality using the fuzzy weighted SERVQUAL method. *Applied Soft Computing Journal, 11*, 2117–2128. https://doi.org/10.1016/j.asoc.2010.07.010

Claire, T., Catherine, G., Thorne, C., & Griffiths, C. (2014). Smart, smarter, smartest: Redefining our cities. In *Smart City: How to create public and economic value with high technology in urban space* (Vol. VIII, pp. 89–99). https://doi.org/10.1007/978-3-319-06160-3_4

Deakin, M., & Al Waer, H. (2011). From intelligent to smart cities. *Intelligent Buildings International, 3*(3), 133–139. https://doi.org/10.1080/17508975.2011.586673

Dhingra, M., & Chattopadhyay, S. (2016). Advancing smartness of traditional settlements- case analysis of Indian and Arab old cities. *International Journal of Sustainable Built Environment, 5*, 549–563. https://doi.org/10.1016/j.ijsbe.2016.08.004

Dhingra, M., & Chattopadhyay, S. (2017). Exploring the real smartness in an urban context through a deductive the real urban smartness). In H. Wang, & S. Ledwon (Eds.), *53rd ISOCARP congress* (pp. 642–652). ISOCARP.

Dhingra, M., Singh, M. K., & Chattopadhyay, S. (2016). Rapid Assessment tool for traditional Indian Neighbourhoods: a Case Study of Alwar walled city in Rajasthan. *Sustainable Cities and Society, 26*, 364–382. https://doi.org/10.1016/j.scs.2016.06.015

Dhingra, M., Kumar, M., Chattopadhyay, S., Singh, M. K., & Chattopadhyay, S. (2017). City, culture and society macro level characterization of historic urban landscape: Case study of Alwar walled city. *City, Culture and Society, 9*, 39–53. https://doi.org/10.1016/j.ccs.2016.10.001

Dubois, D., & Prade, H. (1985). A review of fuzzy set aggregation connectives. *Information Sciences, 36*(1–2), 85–121. https://doi.org/10.1016/0020-0255(85)90027-1

Emmenegger, P., Schraff, D., & Walter, A. (2014). *QCA, the truth table analysis and Large-N survey data: The benefits of calibration and the importance of robustness tests (Issue October)*.

Garau, C., & Pavan, V. M. (2018). Evaluating urban quality: Indicators and assessment tools for smart sustainable cities. *Sustainability, 10*(3). https://doi.org/10.3390/su10030575

Glasmeier, A., & Christopherson, S. (2015). Thinking about smart cities. *Cambridge Journal of Regions, Economy and Society, 8*(1), 3–12. https://doi.org/10.1093/cjres/rsu034

Government of India. (2011). *Census 2011*.

Harrison, K. (2017). Who is the assumed user in the Smart City?. In V. Angelakis, E. Tragos, H. C. Poehls, A. Kapovits, & A. Bassi (Eds.), *Designing, developing, and facilitating smart cities* (Vol. XIV, pp. 17–33) Springer International Publishing. https://doi.org/10.1007/978-3-319-44924-1.

Hassall, J. (1999). Methods of analysing ordinal/ interval questionnaire data using fuzzy mathematical principle. *Management Research Centre Is, 44*.

Herrera, F., Herrera-Viedma, E., & Verdegay, J. L. (1998). Choice processes for non-homogeneous group decision making in linguistic setting. *Fuzzy Sets and System, 94*, 287–308.

Herrera-Viedma, E., Riera, J. V., Massanet, S., Torrens, J., et al. (2014). Some remarks on the fuzzy linguistic model based on discrete fuzzy numbers. In P. Angelov (Ed.), *Intelligent systems* (Vol. 322, pp. 57–68). Springer International Publishing. https://doi.org/10.1007/978-3-319-11313-5.

Hollands, R. G. (2015). Will the real smart city please stand up? *City, 12*(May), 303–320. https://doi.org/10.1080/13604810802479126

Hubert, M., Rousseeuw, P. J., & Branden, K. Vanden (2005). ROBPCA: A new approach to robust principal component analysis. *Technometrics, 47*(1), 64–79. https://doi.org/10.1198/004017004000000563

Jollife, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 374*(20150202). https://doi.org/10.1098/rsta.2015.0202

Klir, G. J., & Yuan, B. (1932). Fuzzy sets adnd fuzzy logic: Theory and applications. In *Geophysical Journal International* (Vol. 189). Prentice Hall PTR. https://doi.org/10.1111/j.1365-246X.2012.05469.x. Issue 3.

Kostof, S. (1991). *The city shaped: Urban patterns and meanings throughout history*.

Lalla, M., Ferrari, D., & Pirotti, T. (2014). Fuzzy inference system to analyze ordinal variables the case of evaluating teaching activity. *Proceedings of the International Conference on Fuzzy Computation Theory and Applications (FCTA-2014)*, 25–36. https://doi.org/10.5220/0005054400250036

Lalla, M., Facchinetti, G., & Mastroleo, G. (2005). Ordinal scales and fuzzy set systems to measure agreement: An application to the evaluation of teaching activity. *Quality and Quantity, 38*(5), 577–601. https://doi.org/10.1007/s11135-005-8103-6

Linting, M., & van der Kooij, A. (2012). Nonlinear principal components analysis with CATPCA: A tutorial. *Journal of Personality Assessment, 94*(1), 12–25. https://doi.org/10.1080/00223891.2011.627965

Macdonald, G. (2016). *Criteria for selection of high-performing indicators: A checklist to inform monitoring and evaluation (Evaluation checklists project)*. https://www.wmich.edu/sites/default/files/attachments/u350/2014/Indicator_checklist.pdf.

Manisera, M., van der Kooij, A. J., & Dusseldorp, E. (2010). Identifying the component structure of satisfaction scales by nonlinear principal components analysis. *Quality Technology & Quantitative Management, 7*(2), 97–115. https://doi.org/10.1080/16843703.2010.11673222

Martin, C. J., Evans, J., & Karvonen, A. (2018). Smart and sustainable? Five tensions in the visions and practices of the smart-sustainable city in Europe and North America. *Technological Forecasting and Social Change, 133*, 269–278. https://doi.org/10.1016/j.techfore.2018.01.005

Martín, J. C., Román, C., & Gonzaga, C. (2018). How diiferent n-point Likert scales affect the measurement of satisfaction in academic conferences. *International Journal for Quality Research, 12*(2), 421–440.

McNeill, F. M., & Thro, E. (1994). *Fuzzy logic- a practical approach*. AP PROFESSIONAL.

Meulman, J. J., Van Der Kooij, A. J., & Heiser, W. J. (2004). Principal components analysis with nonlinear optimal scaling transformations for ordinal and nominal data. *Handbook of quantitative methods in the social sciences* (pp. 49–70). https://doi.org/10.4135/9781412986311. Issue June 2014.

Mohan, I. (1992). *Environmental issues and urban development of the walled cities*. Mittal Publications.

Moore, G. H. (1950). Criteria for selecting indicators. *Statistical indicators of cyclical revivals and recessions* (pp. 20–31).

Neirotti, P., De Marco, A., Cagliano, A. C., Mangano, G., & Scorrano, F. (2014). Current trends in smart city initiatives: Some stylised facts. *Cities, 38*, 25–36. https://doi.org/10.1016/j.cities.2013.12.010

Niskanen, V. A. (2004). In P. J. Kacprzyk (Ed.), *Soft computing methods in human sciences*. Springer-Verlag Berlin Heidelberg GmbH. https://doi.org/10.1007/978-3-540-36421-4.

Prado, A. L., Costa, E. M. D.a, Furlani, T. Z., & Yigitcanlar, T. (2016). Smartness that matter: Towards a comprehensive and human-centred characterisation of smart cities. *Journal OfOpen Innovation: Technology, Market, and Complexity, 2*(8), 1–13.

Prokop, M., & Řezanková, H. (2011). Data dimensionality reduction methods for ordinal data. *International Days of Statistics and Economics Prague*, 523–533.

Rattanalertnusorn, A., Thongteeraparp, A., & Bodhisuwan, W. (2013). Fuzzy rating score on the Likert scale. *Fundamentals and Applied Sciences*, 318–325.

Rice, J. C., & Rochet, M. J. (2005). A framework for selecting a suite of indicators for fisheries management. *ICES Journal of Marine Science, 62*(3), 516–527. https://doi.org/10.1016/j.icesjms.2005.01.003

Romanelli, M. (2020). Towards cities as communities. In Y. Baghdadi, A. Harfouche, & M. Musso (Eds.), *ICT for an inclusive world: Industry 4.0–towards the smart enterprise* (pp. 125–132). Springer International Publishing. https://doi.org/10.1007/978-3-030-34269-2_10.

Selection of Indicators. (2020). *Measure Evaluation*. https://www.measureevaluation.org/prh/rh_indicators/overview/rationale2.

Shelton, T., Zook, M., & Wiig, A. (2015). The 'actually existing smart city'. *Cambridge Journal of Regions, Economy and Society, 8*(March (1)), 13–25. https://doi.org/10.1093/cjres/rsu026

Simo, U. F., & Gwét, H. (2018). Fuzzy triangular aggregation operators. *International Journal of Mathematics and Mathematical Sciences*. https://doi.org/10.1155/2018/9209524

Smithson, M. (1983). Fuzzy set analysis for behavioral and social sciences. *Recent research in psychology*. Springer-Verlag.

Strong, C. (2017). The role of surveys in the age of behavioural science. *Ipsos* (Issue June) https://www.ipsos.com/en/role-surveys-age-behavioural-science.

Tavana, M., Di Caprio, D., & Santos-Arteaga, F. J. (2015). A bilateral exchange model: The paradox of quantifying the linguistic values of qualitative characteristics. *Information Sciences, 296*(1), 201–218. https://doi.org/10.1016/j.ins.2014.10.065

The Social Report 2010, 4 (2010).

Thiem, A., & Dusßa, A. (2013). *Qualitative comparative analysis with r: A user's guide*. SpringerBriefs in Political Science.
Town Planning Department. (2011). *Master plan 2011-2031*.
Trindade, E. P., Hinnig, M. P. F., da Costa, E. M., Marques, J. S., Bastos, R. C., & Yigitcanlar, T. (2017). Sustainable development of smart cities: A systematic review of the literature. *Journal of Open Innovation: Technology, Market, and Complexity, 3* (11). https://doi.org/10.1186/s40852-017-0063-2
Villacorta, P. J., Masegosa, A. D., Castellanos, D., & Lamata, M. T. (2014). A new fuzzy linguistic approach to qualitative Cross Impact Analysis. *Applied Soft Computing Journal, 24*, 19–30. https://doi.org/10.1016/j.asoc.2014.06.025
Vonglao, P. (2017). Application of fuzzy logic to improve the Likert scale to measure latent variables. *Kasetsart Journal of Social Sciences, 38*(3), 337–344. https://doi.org/10.1016/j.kjss.2017.01.002
Yigitcanlar, T. (2015). Smart cities: an effective urban development and management model? *Australian Planner, 52*(1), 27–34. https://doi.org/10.1080/07293682.2015.1019752
Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*, 338–353.
Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning-I. *Information Sciences, 9*(1), 43–80. https://doi.org/10.1016/0020-0255(75)90017-1