Research Paper

A fuzzy-logic-based decision support system for resilient smart city planning

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Abstract

The study develops an intelligent decision-support system to quantify the inherent smartness of a traditional urban system. It strongly emphasizes the importance of integrating complex ecosystems of people, their institutions, and heritage and advocates transdisciplinary soft computational techniques to deal with present day challenges for resilient smart city planning. Four levels of abstraction are identified for the hierarchical evaluation of households' responses within the delineated study area of Alwar walled city in north Indian state of Rajasthan. The residents' perceptions are aggregated using fuzzy arithmetic averaging, which are further aggregated using fuzzy weighted averaging. Assuming this derived value as the response variable, a Sugeno fuzzy inference system is trained using leave-one-out-cross-validation (LOOCV) and optimized using metaheuristics algorithms. A genetic algorithm-based optimized model with urban fabric, network topology, and cultural vitality as independent input variables is proposed to predict inherent smartness quotient of an urban system. Application of partial compensatory approach, fuzzy linguistic variables for aggregation, and non-linear optimization enhance the readability, flexibility, and replicability of the model. The proposed model can provide an effective decision and planning support tool to policymakers and planners and facilitate benchmarking of spatial units to make informed choices, while considering the qualitative and quantitative parameters.

Keywords

Smartness Quotient, Fuzzy Logic, Decision Support Tool, Smart Cities Mission, Humanistic approach

1. Introduction

'Smart City' has become a buzz word in urban policymaking, with strong emphasis on retrofitting network ICT solutions and advanced urban technologies into an existing urban environment (Clark, 2020; Dhingra, 2023). However, many scholars argue that a smart city landscape should be shaped by the local characteristics, priorities, and needs of its citizens instead of random spatial fixes (Hollands, 2008; Yigitcanlar, 2015). A comprehensive and critical literature review of the 'smart city' concept helped identify three research gaps - ambiguity in the 'smart' label, fragmented intervention strategies that miss out critical urban and social aspects, and underutilization of existing cities' potential (Dhingra and Chattopadhyay, 2021a). This ongoing debate envisages a need to develop a methodology for assessing the urban attributes of existing settlements that contribute to the goals of urban smartness. The study aims to develop a composite index that can assess the inherent smartness of a given system, which is referred as smartness quotient (SQ). The consequent goals are to learn about the fundamental concept and objectives of smart urban development, to evaluate existing settlements with a new perspective of development prosperity and potential, and to explore soft-computational methods for making informed urban planning decisions.

Urban smartness should result in certain outcomes, which are nothing but core vision and objectives of smart urbanism (Dhingra and Chattopadhyay, 2021a). Accordingly, a smart city is defined as an urban system that strategically leverages the hidden potential of its existing communities in terms of their social, cultural, economic, environmental, and physical attributes to improve the quality of life and well-being of its citizens, promote urban sustainability, and ensure inclusive socio-economic growth (Dhingra and Chattopadhyay, 2022). Based on the three core guiding principles of urban sustainability, liveability and inclusivity, a pool of indicators is operationalized to a measurable set of variables of interest (Dhingra and Chattopadhyay, 2022). Alwar in the north Indian state of Rajasthan is selected as a case representative of a traditional historic urban landscape (Dhingra et al., 2017). Since historic cities tend to organize themselves in an intuitive and complex manner, collective social attitudes and perceptions of its local communities can help realise their hidden potential.

Such a real-world phenomenon is neither bivalent nor objective, and thus, requires a subjective assessment of people's perception characterized by multi-valued logic, and thus, linguistic variables are preferred instead of their numerical counterparts (Pedrycz and Gomide, 2007). This transdisciplinary research seeks a practical solution for multiple stakeholders to achieve a resilient urban solution for today's urbanization and sustainability challenges. Fuzzy logic is found to be equipped to deal with epistemic uncertainty, ambiguity, and non-linearity in the actual world (Vonglao, 2017; Zadeh, 1975). A groundwork for background assessment of existing communities to embrace urban innovation and technological interventions is laid out to assist the urban local bodies and planning experts for adopting localised smart interventions. It also aligns with the ongoing UN-Habitat's people-centred smart cities program, India's 100 smart city mission and increasing global emphasis on sustainable digital transition. The paper is structured into five sections presenting the background research on smart cities from a critical standpoint and introduction to the ongoing Smart Cities Mission (SCM) in India, followed by an overview of case study, methodology, results, and conclusions.

2. Literature Review

2.1. Concept of Smart Cities

There has been a tendency to give more attention to massive urban data instead of urban geography, sociology, history, economics, anthropology, and policymaking for smart city interventions (Batty, 2013). Going by this virtue, technology becomes the goal for many cities, keeping the stakes very high for real people and existing places (Mansoor et al., 2015; Shelton et al., 2014). Inefficient incorporation of ICT within an existing spatial setting can result in a loose, fragmented, polycentric, and complex urban form with fast dispersing and de-concentrating land uses, social and spatial segregation, congested streets, and disappearing open spaces (Audirac, 2005). A comparison between the rhetoric targets and the real outcomes of some of the global smart city interventions indicates an acritical, ahistorical, and aspatial understanding of spatial data (Dhingra and Chattopadhyay, 2022). Also, such interventions can give internally differentiated results within a city by privileging some places, people, and activities over others (Shelton et al., 2014).

The first objective of the study is to understand and synthesize the real meaning of urban smartness. Dhingra & Chattopadhyay (2021) adopted a comprehensive systematic literature search and review method coupled with a content analysis using inductive grounded theory and deductive text mining for meta-synthesis. The missing urban dimensions from the present smart city framework against the existing dimensions are identified using Dooyeweerd (2010) integrative model and experts' surveys. The results show that spatial and cultural factors are yet not given enough importance in the smart city framework.

Also, the critical arguments and evidence related to the smart city research were weighed and substantiated by identifying expected outcomes and characteristics of smart cities. The graphical representation in **Figure 1** summarizes the tripartite vision of smart cities (Dhingra and Chattopadhyay, 2022, 2023). Conceptually, it intends to represent that together sustainability, liveability and inclusivity may indicate the cumulative goals of urban smartness.

Since sustainability is mostly associated with the tangible aspects of a place, liveability subsumes how people perceive their residential environment, and inclusivity is more about equality and parity experienced by all citizens, the model is assumed at the cross-section of 3Ps- People, Place, and Parity, which are also the missing urban dimensions in the present smart city framework. Under the aegis of the tripartite smart city model, 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 (Dhingra and Chattopadhyay, 2021b, 2021c). Consequently, a pool of indicators using keyword search are prepared under social, economic, environmental, mobility, living, governance, physical, and cultural dimensions. These variables are further classified into cognitive, factual, and spatial based on their data type and possible data collection instruments. Subsequently, these variables are operationalized into a final set of ten SUAs with 35 indicators and 118 variables, given in **Table 1,** based on their spatial relevance, frequency, specificity, measurability, and data collection feasibility. The**.**

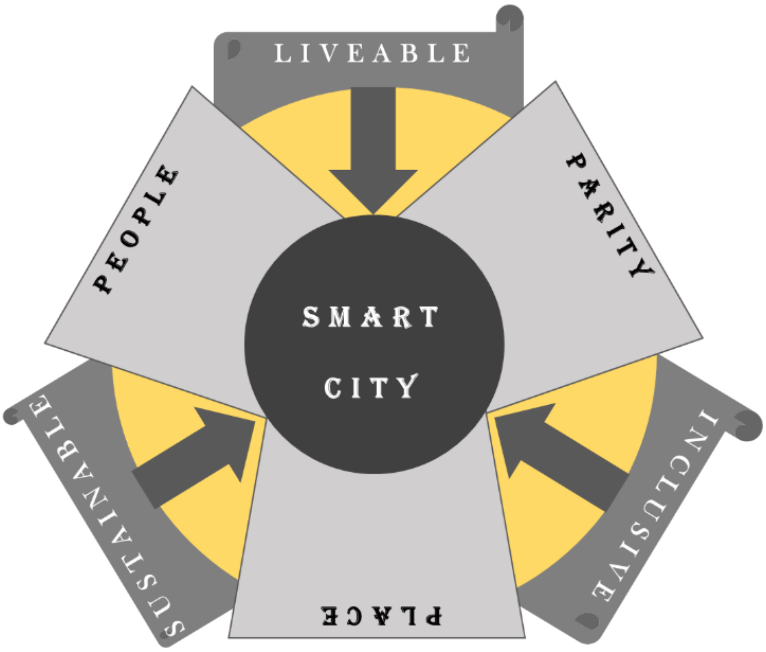


Figure 1. A tripartite smart city model. Source: Dhingra and Chattopadhyay (2023).

Table 1. List of SUAs and Indicators. Source: Authors.

Smart Urban Attribute (SUA)		Indicator	
SUA 1	Local Environmental Quality	C01	Comfortable Temperature
		C02	Low Level of Noise
		C03	Low Local Pollution
SUA 2	Sense of Safety and Security	C04	Perceived Safety
		C05	Local Surveillance
SUA 3		C06	Performance of basic services

	Perceived Residential Environment	C07	Quality of Urban Spaces
SUA 4	Collective Efficacy and Social Cohesion	C08	Low Resident Mobility Rate
		C09	Degree of Tolerance
		C10	Incidences of Social Interaction
		C11	Degree of interpersonal trust
SUA 5	Cultural Vitality	C12	Cultural Freedom
		C13	Sense of Belongingness
		F1	Cultural Significance
		F2	Economic Contribution
SUA 6	Accessibility	C14	Travel Behavior
		F3	Travel Behavior
		S1	Road Network Density
		S2	Intersection Density
		S3	Connectivity
		S4	Centrality Measures
		S5	Network Topology
		S6	Detour analysis
		S7	Availability of facilities
		S8	Proximity to nearest facility
SUA 7	Compactness	S9	Perimeter Index
		S10	Exchange Index
SUA 8	Density	S11	Morphological Density
		S12	Neighborhood Density
		S13	Jobs Density
SUA 9	Green and Open Spaces	S14	Porosity Index
		S15	Greenness Index
SUA10	Diversity	S16	Land use mix Index
		S17	Intensity of Development
		S18	Clustering Index

2.2. India's Smart Cities Mission

The policy implications of this study can be understood from the perspective of the ongoing Smart City Mission (SCM) in India. The Government of India has realized the economic potential of its urban centres and announced this national program to assist states and local authorities in building 100 world-class smart cities (Aijaz, 2021; Das, 2020) The various features of a smart city as identified by the ministry are represented in **Figure 2** with frugal innovation at the centre (NASSCOM, 2015). Cities were shortlisted based on the urban population and number of towns in the state followed by an inter-jurisdictional smart cities challenge where all cities compete (Government of India, 2020).

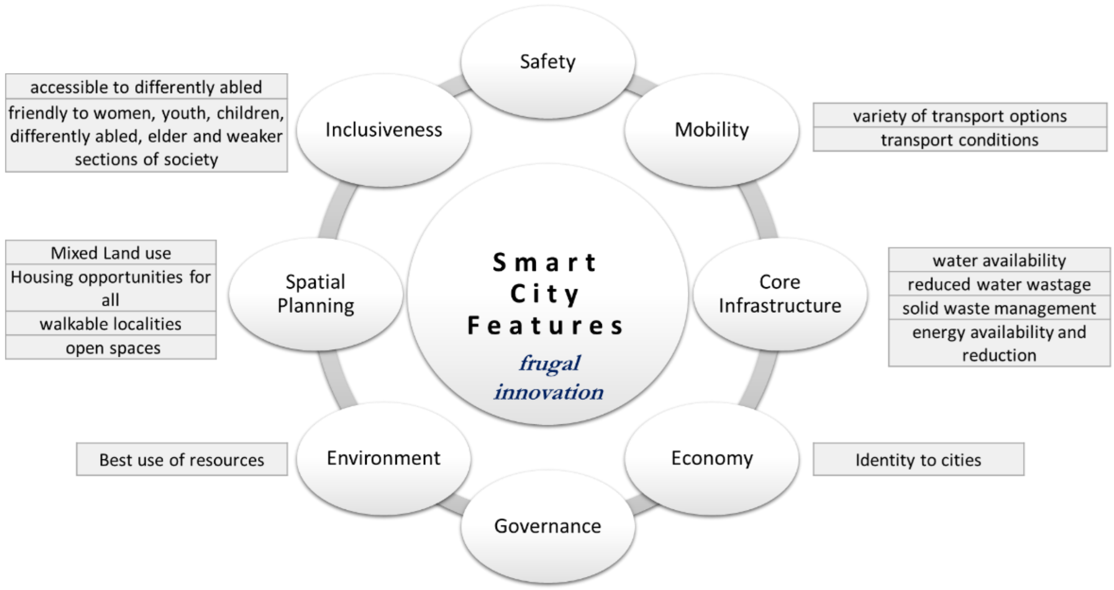


Figure 2. Features of smart cities under Smart Cities Mission of India. Source: adapted from Government of India (2020).

A SWOT analysis of the ongoing SCM is shown in **Figure 3**. The mission's overall approach has diluted the overly critical role of urban experts and planning documents to build smart city proposals. The projects under the mission focus on pan-city innovation and area-based development, for which primarily cities have relied on citizens' voting to identify problematic areas and sectors for intervention in their respective cities. But this approach can also result in a biased solution, representing a minor section of digitally literate society. City authorities also seek to replicate the ICT solution in other areas with time, but the possibility of spatial inequalities and digital divides have been ruled out and no incremental model of deployment and maintenance of urban technologies is discussed. Undeniably, the ideas developed for western counterparts and greenfield developments may not translate perfectly to the existing communities in India.

STRENGTHS	WEAKNESSES	OPPORTUNITIES	THREATS
• Shift in focus from greenfield to retrofitting and redevelopment strategies • Spatial planning and people-centric approach are important elements • Holistic vision is laid-out with focus on core urban infrastructure as well as the soft non-technical attributes of cities • Detailed and systematic guidelines along with ample technical resources are easily accessible	• No explicit linkages between SCP and master plan documents • Public voting used for identification of areas and sectors for development, leading to biased choices • Missing technical and planning expertise • Smart solutions to be replicated but no discussion about the incremental approach • O&M costs of ICT hardware not considered	• Potential to tap technical expertise and financial resources of private players • Multi-stakeholder approach paves way for an inclusive city-making • Smart citizenship • Create an efficient urban management system • Enhance the capacity of urban institutions • Inherent smartness of existing cities can be channelized	• Area-based approach leading to spatial inequalities and uneven innovation • ICT may take the front seat, missing out critical socio-economic determinants of cities • Cultrual capital at risk in the race of bulding world class cities • Marginalized and urban poor may get neglected • Privatization of public services • Blind faith in ICT to solve urban problems

Figure 3. SWOT Analysis of SCM. Source: Authors.

3. Case of Alwar walled city in Rajasthan, India

Alwar in the north Indian state of Rajasthan is selected as case study representing a traditional walled city. It is also one of the regional priority towns under the National Capital Region of Government of India. The city is around 200 centuries old with strong traditional roots, a rich residential culture of neighbourhoods (indigenously called mohallas), a unique way of life, and culturally significant economic activities (Dhingra et al., 2017, 2016; Dhingra and Chattopadhyay, 2016). The inputs from the experts' surveys, field surveys, cognitional mapping, and pilot surveys assist in delineating the soft boundary for the study area. **Figure 4** illustrates the location of the case study.

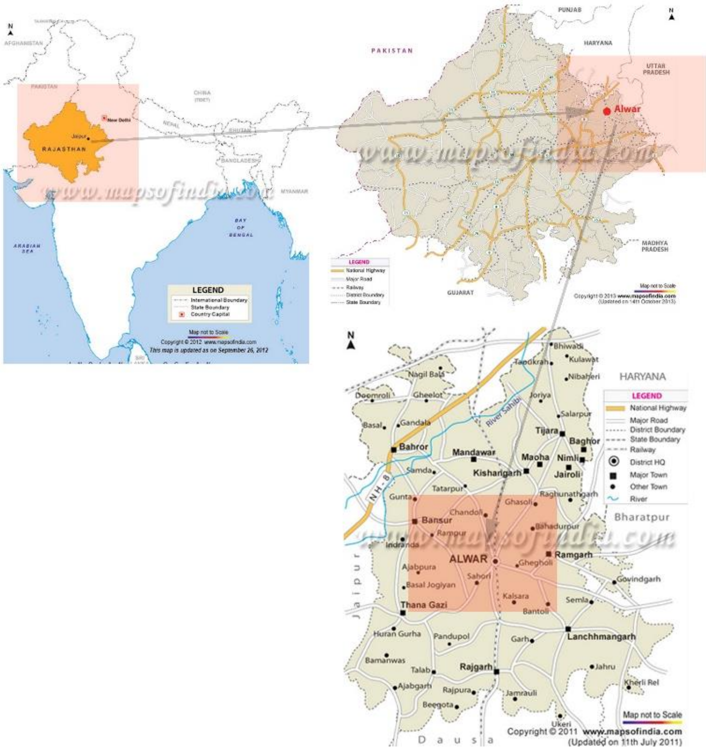


Figure 4. Location of case study. Source: adapted from www.mapsofIndia.com.

The structure of mohallas is characterized by squares (chowks), winding streets, mixed land use, and tangible and intangible heritage components. The spatiotemporal assessment of the case study shows a relatively better performance of traditional settlements in terms of perimeter index, density, clustering indices, green spaces, and network topology (Dhingra and Chattopadhyay, 2022). The traditional settlements have an integrated street network conducive to pedestrian movements with respect to their syntactic and geometrical properties, indicating overall high intelligibility. **Figure 5** gives a glimpse of various tangible and intangible heritage components of the city.

Figure 5. Tangible and Intangible Heritage. Source: Authors.

4. Methodology

Figure 6 represents the detailed methodological approach adopted for the development of an intelligent fuzzy system model for predicting SQ value of geographically defined spatial units referred as Neighbourhood Planning Units (NPUs) for the study area. A flexible, interpretable, and conceptually comprehensive methodology is devised to collect data using fuzzy linguistic variables through residents' perception surveys, quantify them using fuzzy aggregation operators, devising their equivalent linguistic labels for better readability, and subsequently developing a predictive SQ model, which should be able to take relevant inputs from the users and result in SQ as the output values. Four levels of abstraction are identified for the hierarchical evaluation and residents' perceptions are aggregated using fuzzy arithmetic averaging, which are further aggregated using fuzzy weighted averaging.

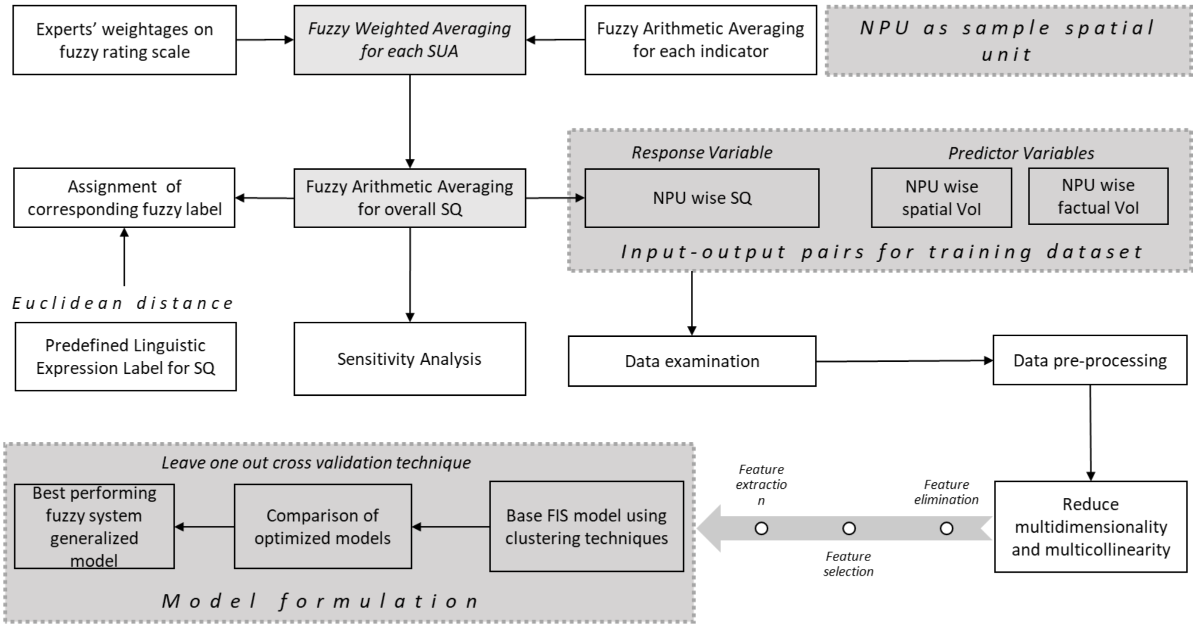


Figure 6. Detailed methodology for construction of model. Source: Authors.

With the help of cognitional mapping and field surveys, boundaries of eighty perceived neighbourhoods are mapped using ArcGIS. These neighbourhoods represent traditional constructs of the image of a mohalla in the minds of its residents. Also, other intangible elements of urban heritage, such as customs and beliefs, are quantified based on experts' interviews, focus group discussions, qualitative studies, and secondary data analysis. The binarized values of perceived mohallas were subsequently used for their clustering into NPUs using the k-nearest neighbour algorithm. **Figure 7** represents 30 NPU boundaries derived based on their value-based assessment.

Around 400 household surveys (calculated using Cochran's formula) were conducted using a simple random sampling technique within the delineated study area to capture the perceptions of its inhabitants about their residential environment corresponding to cognitive variables such as a sense of safety, belongingness, and interpersonal trust. While coding the output, the answer of the i^{th} respondent corresponding to j^{th} indicator and k^{th} variable gives an outcome $\tilde{R}_j$, in the range of {2, 4, 6, 8, 10} on the Likert scale. Assuming symmetric triangular fuzzy numbers (TFN), fuzzy set of responses can be denoted as $\tilde{R}_i$=SD, D, N, A, SA- TFN_{SD}(0, 2, 4) (strongly disagree), TFN_D(2, 4, 6) (disagree), TFN_N(4, 6, 8) (neutral), TFN_A(6, 8, 10) (agree) and TFN_{SA}(8, 10, 10) (strongly agree) **(Figure 8)** (Dhingra and Chattopadhyay, 2021b). The data collected on the Likert scale during the households' surveys was fuzzified using a fuzzy conversion scale, which was further assessed using fuzzy aggregation techniques. The aggregated score of k^{th} variables results in a generalized mean score for its corresponding j^{th} indicator.

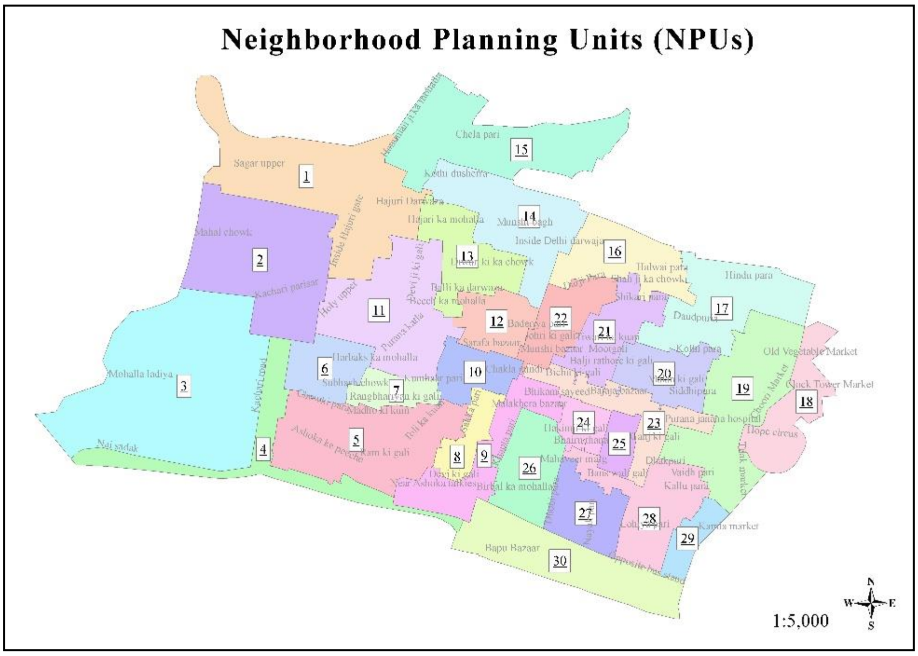


Figure 7. Delineated NPUs. Source: Authors.

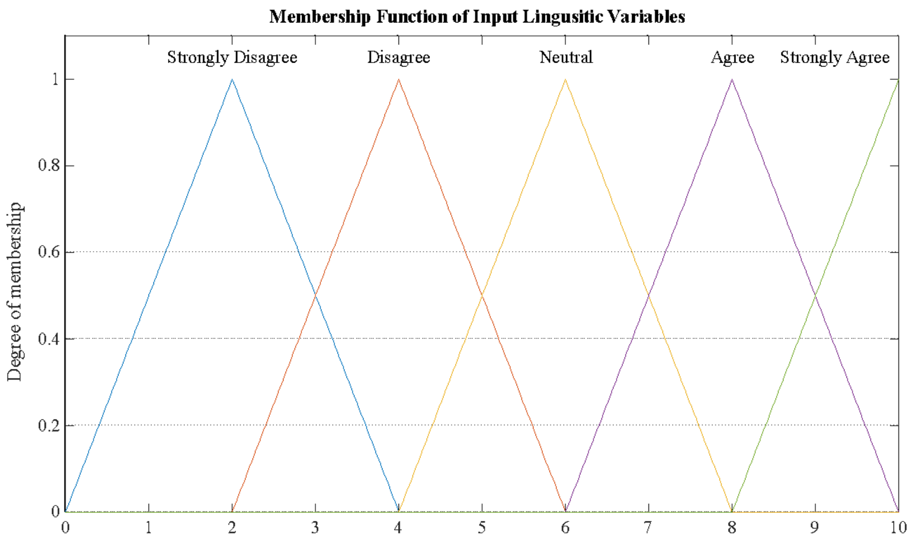


Figure 8. Fuzzy conversion scale for Likert scores. Source: Authors.

Fuzzy arithmetic averaging (FAA) on k linguistic variables assumes equal importance of all the items whereas Fuzzy Weighted Average (FWA) is subsequently used to account for each indicator's relative performance, and subjective scoring by experts (Guh et al., 2008). Assuming residents' satisfaction as a proxy of smartness, the SQ index is estimated for each NPU, which are further superimposed on a predefined linguistic scale of smartness for assigning a linguistic label to each SUA. This study proposes five linguistic constants over the universe of discourse referred to as predefined language expression label (PLEL) on which SQ is defined- very low SQ (VLSQ) - TFN(0, 2, 4), low SQ (LSQ) - TFN(2, 4, 6), moderate SQ (MSQ) - TFN(4, 6, 8), high SQ (HSQ) - TFN(6, 8, 10), and very high SQ (VHSQ) - TFN(8, 10, 10), as shown in **Figure 9.** The estimated SQ scores on a scale of 0 to 10 are superimposed over the universe of discourse and a linguistic label is assigned based on the maximum similarity between a linguistic constant and estimated SQ (Hendiani & Bagherpour, 2019; Vinodh & Balaji, 2011). The smaller the Euclidean distance between them, the higher the similarity measure.

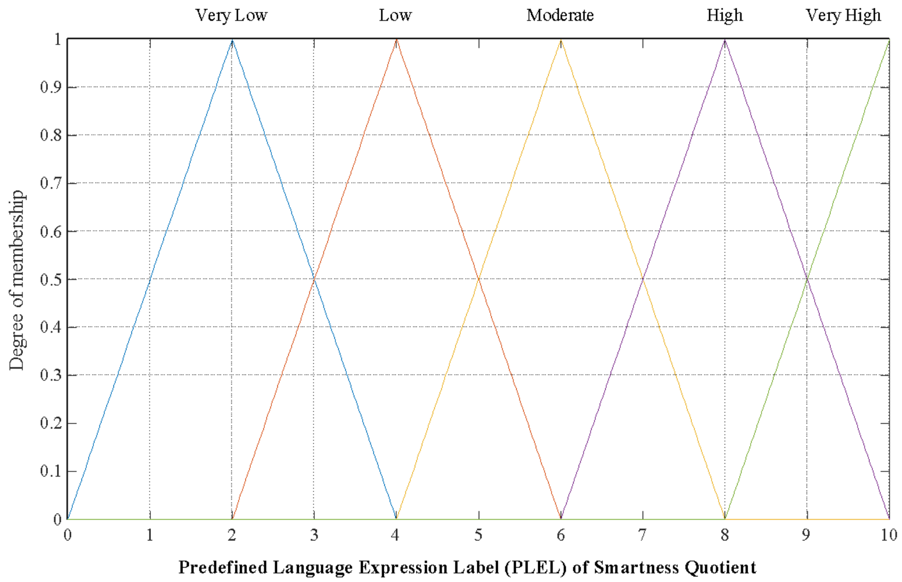


Figure 9. Linguistic constants for SQ. Source: Authors.

Further, the methodology is extended to develop a fuzzy inference system (FIS) as a decision-support tool that allows mapping of numeric inputs and respective linguistic SQ label. The fuzzy SQ scores derived from the simple fuzzy aggregation operations are assumed to be the output values and quantitative data obtained from the spatial analysis and surveys is assumed to be the input values. To develop a generalized model, which can predict SQ for a spatial unit, the factual and spatial variables are used as independent input variables for each NPU as a sample spatial unit. The initial dataset for analysis consists of 74 independent continuous predictor variables against the SQ of each NPU as the dependent response variable. The final processed dataset comprises of uncorrelated five principal components corresponding to network topology, clustering, compactness, density, cultural vitality, and accessibility as predictors of inherent smartness against 1 SQ output, normalized in the range 0 to 1 using the min-max function.

A Sugeno-type FIS base model is initialized and proposed for the study as it is computationally efficient and works well with linear optimization and adaptive techniques with guaranteed continuity of the output surface and better approximation accuracy (Ojha et al., 2019). Six metaheuristic algorithms are applied to the base model for further optimization viz. genetic algorithm (GA), particle swarm optimization (PSO), pattern search (PS), simulated annealing (SA), Artificial Neural FIS (ANFIS) with least square estimation and backpropagation, and ANFIS with backpropagation. Each model is compared in terms of their RMSE, MAE, R^2 and computational efficiency for their overall performance. This hierarchical evaluation doesn't only show the scores at various levels of indicators but also extends to highlight the spatial pattern of each SUA and indicator, acting as a dashboard to assess and monitor the performance of NPUs in different areas of improvement.

5. Results and Discussion

The perception analysis shows a high ranking of cultural vitality, collective efficacy, social cohesion, local environmental quality, and travel behaviour (Dhingra and Chattopadhyay, 2021b). The degree of tolerance, perceived safety, and cultural freedom rank highest amongst indicators while the quality of urbanscape, performance of basic services, and local surveillance didn't perform so well. However, the median score of indicators is 8.59 on a scale of 10, which is quite high in terms of overall neighbourhood satisfaction amongst its residents. **Table 2** shows that most of the SQ values are closer to the HSQ label, while SUA 2 (sense of safety and security) is near MSQ label and SUA 5 (cultural vitality) is near VHSQ label. A graphical representation of the overall SQ superimposed on PLEL membership functions is shown in **Figure 10**, suggesting most of the overlap between derived SQ and the HSQ label.

Table 2. Assignment of a linguistic label. Source: Authors.

SUA		Euclidean distance from PLEL					Linguistic label	Euclidean distance from PLEL					Linguistic label
SUA_i		D(SQ, VLSQ)	D(SQ, LSQ)	D(SQ, MSQ)	D(SQ, HSQ)	D(SQ, VHSQ)	*Present Status*	D(SQ, VLSQ)	D(SQ, LSQ)	D(SQ, MSQ)	D(SQ, HSQ)	D(SQ, VHSQ)	*Present Status*
SUA 1	Local Environmental Quality	11.18	7.73	4.31	1.17	1.72	*High Smartness Quotient*	10.18	6.74	3.35	1.01	2.65	*High Smartness Quotient*
SUA 2	Sense of Safety and Security	8.91	4.13	2.24	1.95	3.90	*High Smartness Quotient*						
SUA 3	Perceived Residential Environment	8.03	3.59	1.21	2.44	4.82	*Moderate Smartness Quotient*						
SUA 4	Collective Efficacy and Social Cohesion	11.29	6.41	4.44	1.37	1.57	*High Smartness Quotient*						
SUA 5	Cultural Vitality	11.41	6.51	4.58	1.52	1.43	*Very High Smartness Quotient*						
SUA 6	Accessibility	10.26	5.46	3.43	0.97	2.58	*High Smartness Quotient*						

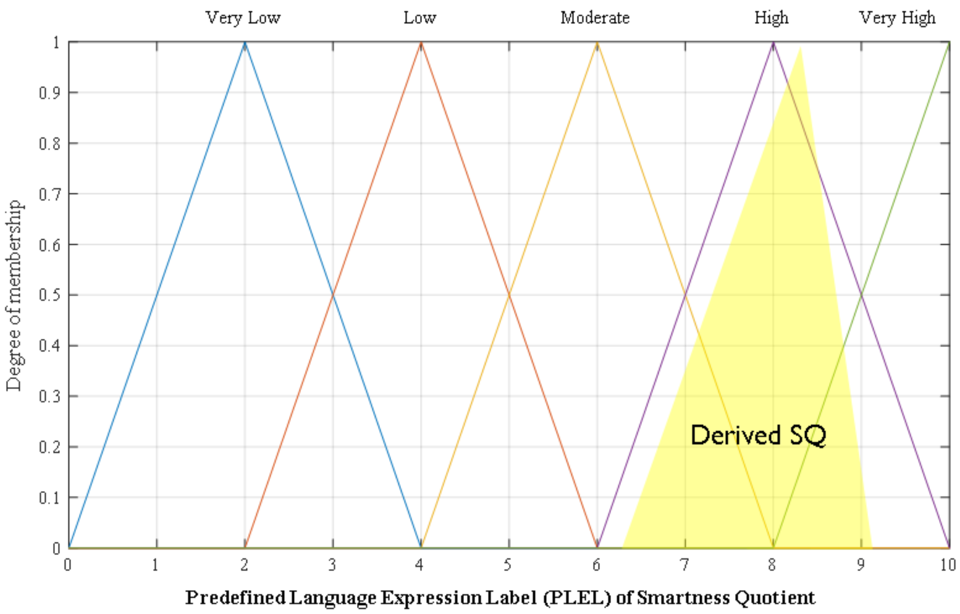


Figure 10. Derived SQ superimposed over PLEL of SQ. Source: Authors.

The SQ of each NPU is also calculated using the proposed methodology and further represented spatially with help of normalized choropleths. **Figure 11** shows SQ distribution for SUA 1: Local environmental quality, which is aggregated score of indicators- comfortable temperature, low local pollution, and low level of noise.

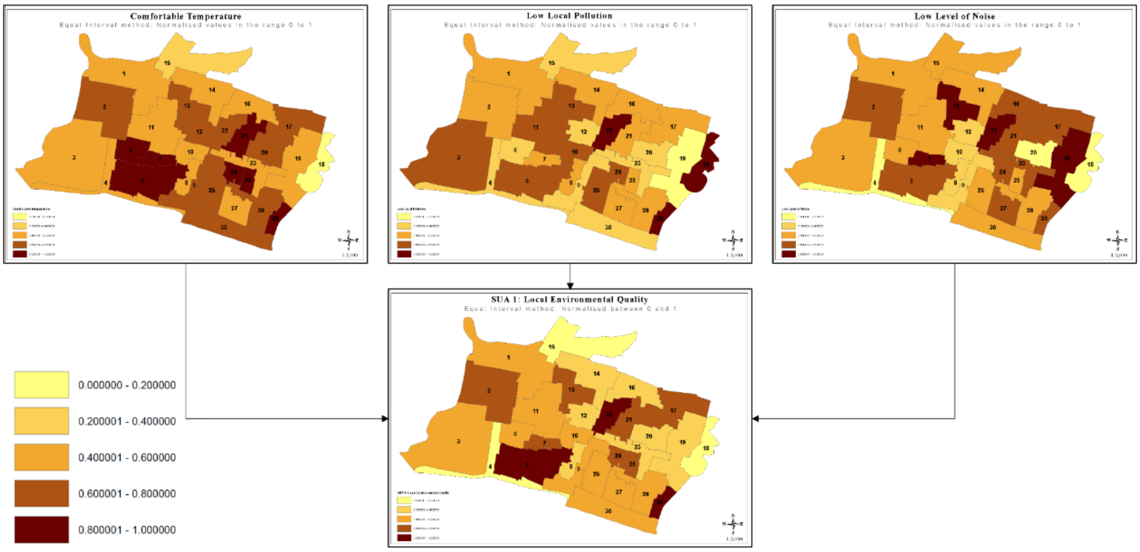


Figure 11. SUA 1: Local environmental quality. Source: Authors.

Figure 12 shows the distribution of SUA 2: Sense of safety and security, which is an aggregated score of perceived safety and local surveillance. Although perceived safety is high for some NPUs, the overall sense of safety is reduced due to low scores of local surveillances.

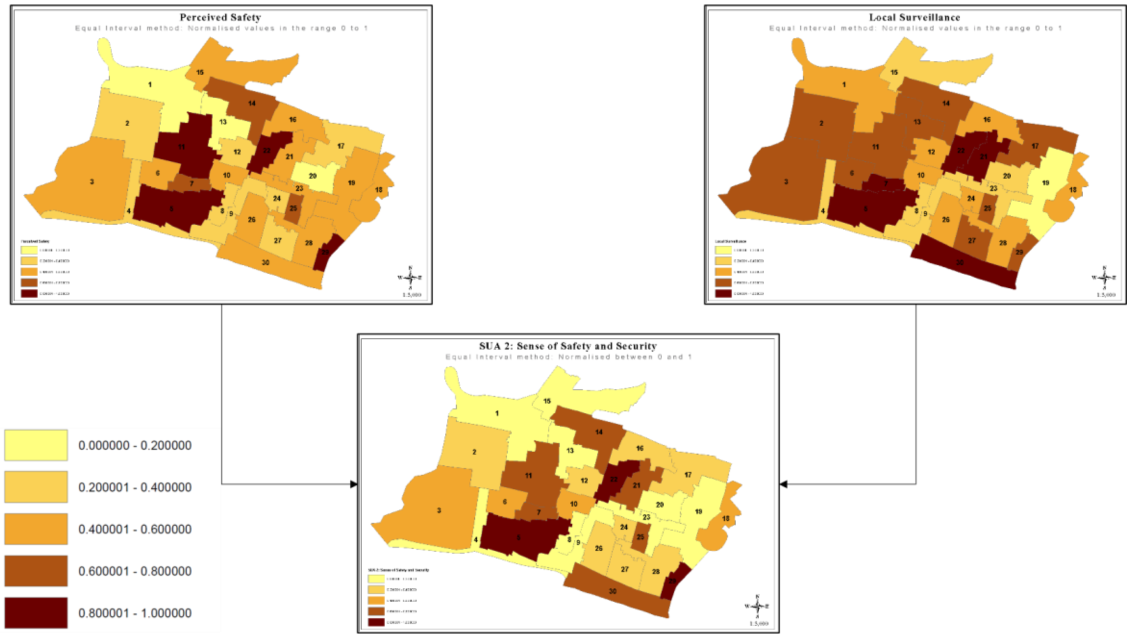


Figure 12. SUA 2: Sense of safety and security. Source: Authors.

Figure 13 shows the distribution of SUA 3: Perceived residential environment, which has the least SQ score amongst all SUAs. The quality of urban spaces scores well, but the performance of ULBs in providing basic services brought the overall SQ down.

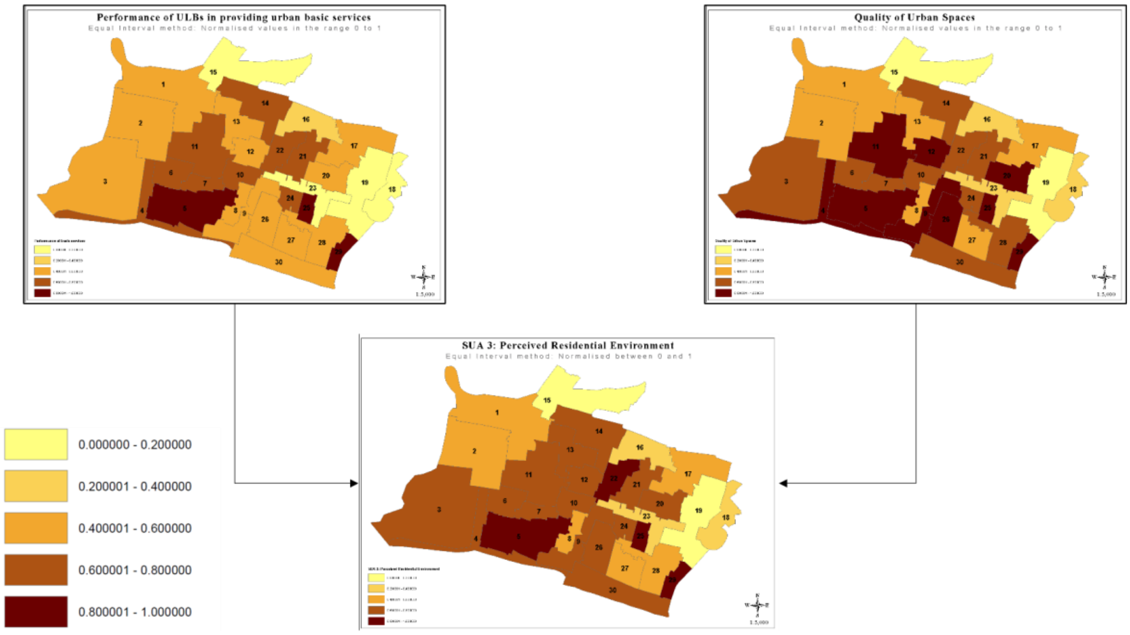


Figure 13. SUA 3: Perceived residential environment. Source: Authors.

Figure 14 shows the distribution of SUA 4: collective efficacy and social cohesion, comprising five indicators- degree of tolerance, incidences of social interaction, degree of interpersonal trust, and low residential mobility rate. The social interaction doesn't perform well while the rest perform satisfactorily.

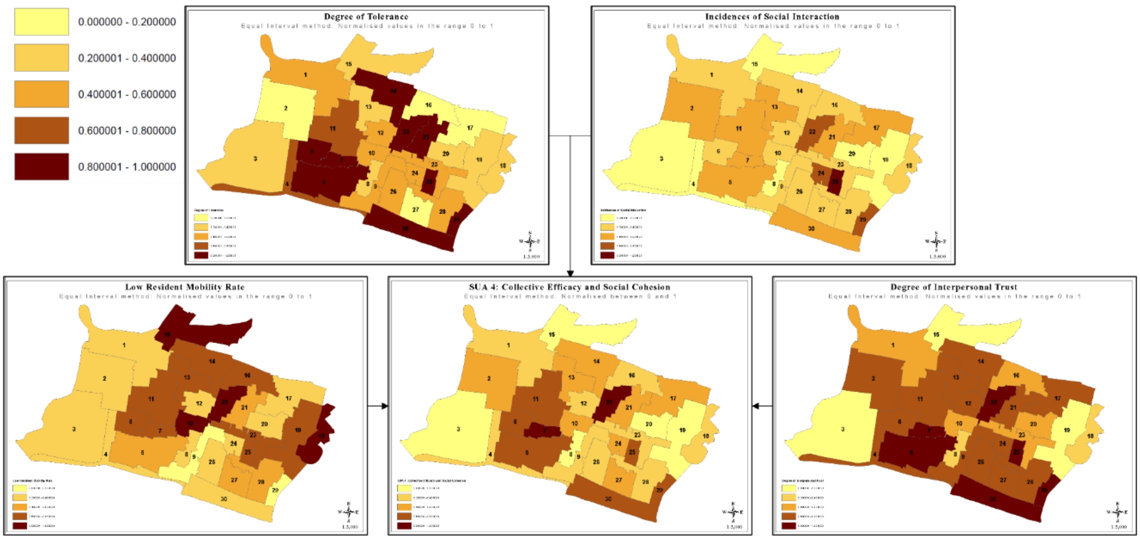


Figure 14. SUA 4: collective efficacy and social cohesion. Source: Authors.

Figure 15 shows the distribution of SUA 5: cultural vitality, which has performed the best amongst all the SUAs, especially due to the very high scores of sense of belongingness.

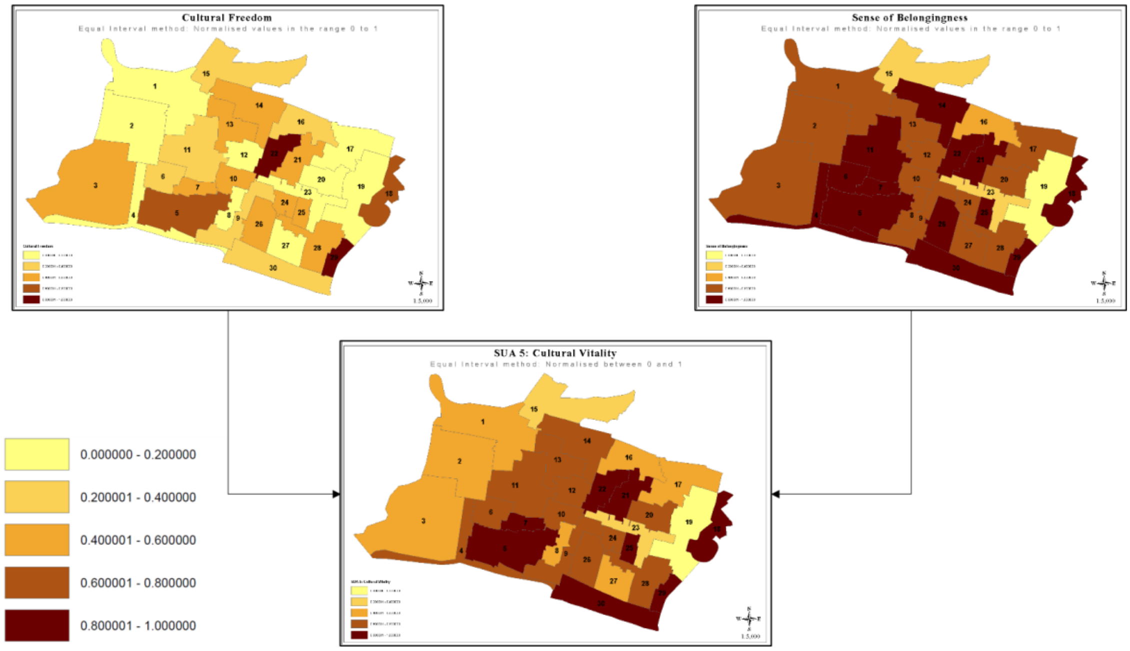


Figure 15. SUA 5: Cultural vitality. Source: Authors.

Figure 16 shows the distribution of SUA6: accessibility comprising travel behaviour as the indicator. Since this is the only indicator under SUA6 in terms of cognitive variables, the normalized fuzzy weightages have changed the overall score of SUA. Even then, many NPUs perform well in terms of the travel choices made by the residents.

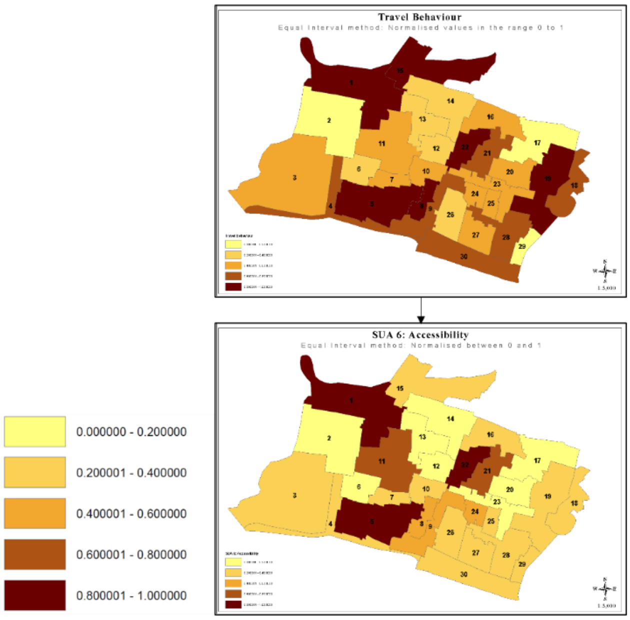


Figure 16. SUA6: Accessibility. Source: Authors.

Figure 17 shows the distribution of the overall SQ of the study area, which is FAA of six SUAs, explained above. NPUs 5 and 12 demonstrate an overall best performance, while NPUs 15 and 19 demonstrate an overall worst performance. NPUs 5 and 12 are old mohallas that have thriving traditional activities and vibrant residential culture. On the other hand, NPU15 is the mohalla situated at the boundary of the walled city and is primarily residential with new gentry, and NPU 19 is an important part of CBD, which has numerous commercial activities in the narrow lanes. This spatial assessment can be used to backtrack the root causes of urban problems in each scenario.

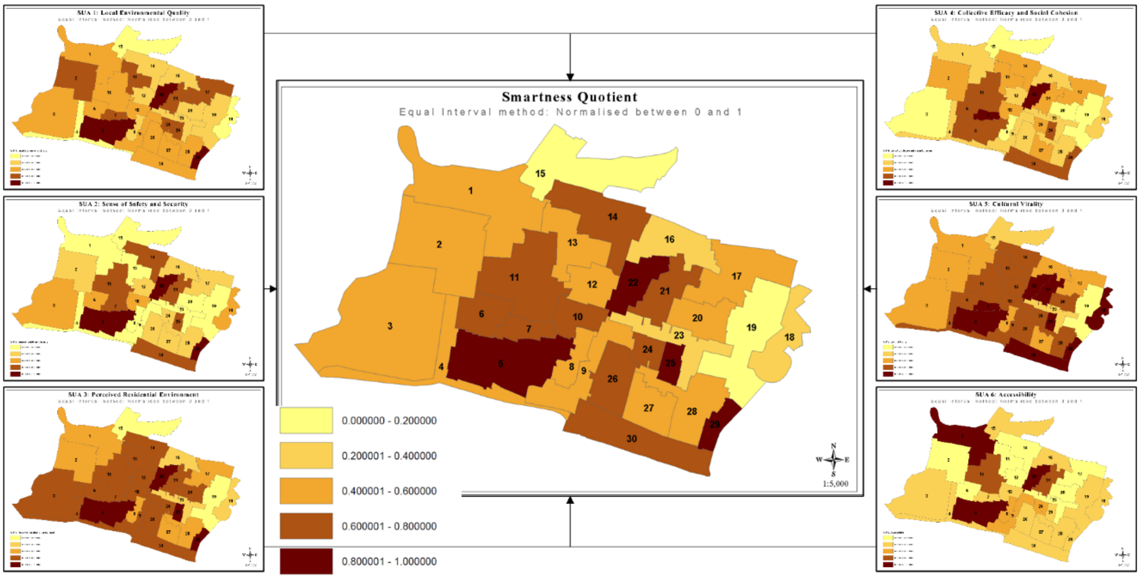
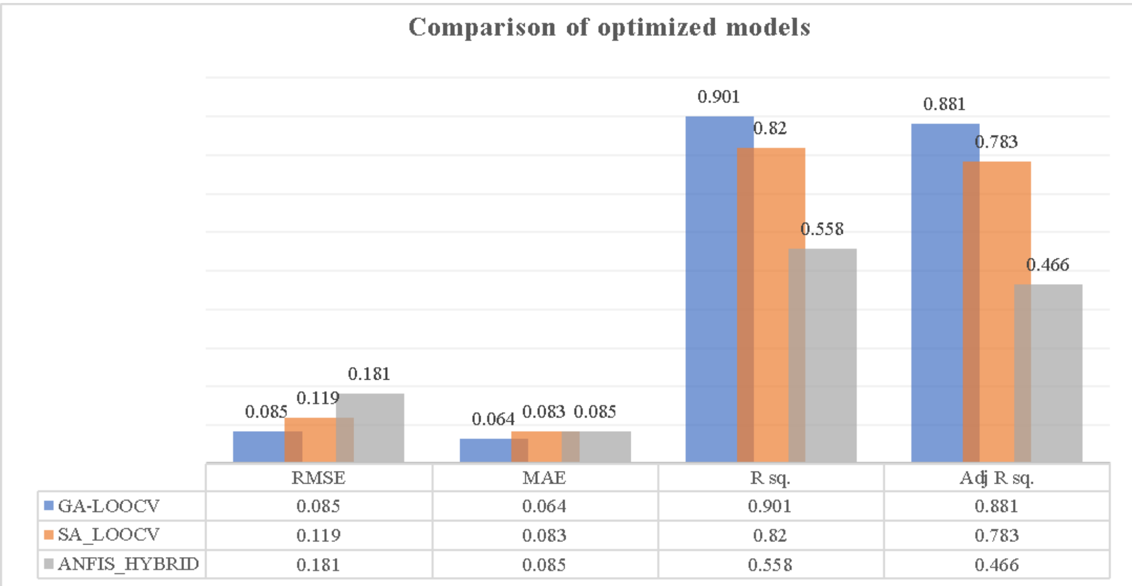


Figure 17. Overall SQ. Source: Authors.

The methodology is extended to non-linear mapping of numeric inputs but linguistic SQ output. **Figure 18** shows the three best-performing models and suggests that the error introduced by the GA-LOOCV model is lowest at 0.085 followed by SA-LOOCV at 0.119 and ANFIS-Hybrid at 0.181. For a single random iteration, the least error is reported by GA-LOOCV with ~90% explained variance and ~91.5% accuracy. The SA-LOOCV model has exceptionally high computational cost in terms of training and validation time, although with ~88% accuracy, whereas the ANFIS-Hybrid model has an exceptionally low computational cost with ~82% accuracy. However, ANFIS-Hybrid results show an overfitted model with zero training error but substantial testing error. Therefore, a GA-based FIS model is proposed as the best performing synergistic model for predicting the inherent SQ of a spatial entity. The proposed model explains ~83% of the total variance and results in the minimum error in comparison to other optimization algorithms. The base model explained 32.6% variance in the dataset, while the optimized model could explain 82.7% variance.



	RMSE	MAE	R sq.	Adj R sq.
GA-LOOCV	0.085	0.064	0.901	0.881
SA_LOOCV	0.119	0.083	0.82	0.783
ANFIS_HYBRID	0.181	0.085	0.558	0.466

Figure 18. Best performing optimization algorithms. Source: Authors.

6. Conclusion

The overall narrative of smart cities shows that there is some major problem with the idea of singularly focusing on technology as the solution, assuming physical planning interventions and urban policymaking are not capable of giving better alternative solutions. This ongoing dilemma, growing interest, and expansion of this concept called for the active role of city experts to identify hidden opportunities within existing settlements. A reconceptualized vision with a focus on missing urban elements and its core objectives is used to derive a set of indicators for assessment of smart urban attributes. Choosing fuzzy logic to develop the methodological approach largely depends on the vague characteristics of the term 'smart' and people's perceptions as well as is guided by a need for an easy-to-read linguistic output.

The study concludes that the existing traditional communities are indigenously smart. Thus, it is imperative to capitalize on the existing social and cultural resources of old cities, rather than merely fixing the spatial setting with technology. An understanding of the zero-level layer of an urban system provides opportunities for urban professionals for advancing it to another level of smartness by planning interventions through a resilient planning approach. The aggregated SQ is around 17% sensitive to variations in the input variables, but the application of fuzzy linguistic labels makes it robust enough to handle minor perturbations. However, the only limitation is that the input data type is fuzzy and therefore, the methodology is extended to develop a fuzzy inference system for non-linear mapping of numeric inputs and fuzzy SQ output.

The theoretical framework is not biased and focuses on an integrative framework of the objectives of smart cities. A partial compensatory approach enables the selection of suitable variables of interest from the vast pool of indicators prepared using the re-conceptualized vision of smart cities, thus lending flexibility and replicability to the proposed model. The model can provide an effective decision and planning support tool to planners and policymakers and facilitate benchmarking and monitoring of the performance of existing neighbourhoods to make localised informed choices. For SCM of India, instead of going for simple voting, which might result in biased priorities, the ULBs can aggregate the citizens' and experts' perspectives into a composite index. The final output can be further conveyed as linguistic labels for each city or neighbourhood instead of mere ranking, thus classifying them based on their smartness quotient, while considering in-built resilience within existing communities. The study persuades city experts to acknowledge the opportunities and challenges of building smart cities and strengthen the role of people, communities, and their longstanding heritage in city-making strategies.

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