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FUZZY BASED DECISION-MAKING ALGORITHM FOR SOLVING BIG DATA ISSUES IN SMART CITIES

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Abstract. To better provide urban services and build an increasingly sustainable architecture, big data can be used to make more efficient use of current assets while enhancing the caliber of services offered to local inhabitants. However, there are several challenges to incorporating big data into existing infrastructure. Therefore, this research aims to determine the problems associated with Big Data's effectiveness in developing intelligent towns and to investigate the connections between those difficulties. The 14 issues with Big Data were found through a literature study, and the precision was checked by feedback from professionals. Next, we employ a combined approach based on fuzzy interpretation, Structured simulation, and the Fuzzy Making Decisions Trial and Assessment Laboratories to decipher the connections between our identified problems incorporating Big Data into the development of smart cities is hampered, as shown by the analysis of links between challenges, primarily by the heterogeneous inhabitants in developed cities and the lack of connectivity. The findings of this study will provide creative city practitioners and policy planners with the information they need to successfully tackle these obstacles, clearing the way for the widespread adoption of smart city technologies. This research is a first step towards creating an interpretive structural model of the difficulties brought on by Big Data in cutting-edge urban planning. The study attempts, in part, to use this paradigm to better understand the relationship among the highlighted issues.

Key words: Big Data, Difficulties, Environmental Sustainability, Intelligent towns, Fuzzy DEMATEL, and Fuzzy Interpretation Structured Modelling (fuzzy ISM)

1. Introduction.

The innovative town concept offers a practical solution to the issues of rapid global urbanization. The IoT, artificial intelligence (AI), and information analysis are just a few of the latest technological advances cities worldwide are exploring to improve a wide range of services municipalities provide. Municipalities also aggressively promote the use of digital technology to advance modernization and the creation of novel business models, with the goals of strengthening regional economies and enhancing social well-being. The smart city market is growing, but there is a concomitant fragmentation of smart city markets and programs, which raises concerns about administration, environment coordination. Transforming a municipality into a "smart city" is a lengthy and complicated endeavor that necessitates the involvement of several stakeholders and the ability to evaluate the potential of numerous novel digital technologies to improve a wide range of municipal operations. The smart city's management and leadership are significantly taxed as a result. This research aims to aid municipalities in accomplishing this objective by providing a smart city conceptual model [1,2,3,4].

In order to help participants in smart cities guide their communities towards a smart city supported by data and digital technologies, SCCM studies complex smart cities from both an organizational and a technical perspective. SCCM considers four main factors: strategy, technology, governance, and stakeholders. Each central element is accompanied by supporting aspects, which collectively generate substantial connections and provide a comprehensive and methodical approach to smart city strategy, creation, and deployment [5-6]. To enhance smart city design and ecosystem governance, this study created and presented a smart city conceptual model (SCCM). The Smart City Change Management (SCCM) framework was created because urban areas lack the resources to manage sophisticated smart city ecosystems and the rapid advancement of digital technologies. These issues cause a high rate of premature smart city initiatives to collapse once project funding has been depleted. The primary goals of the Smart City Capacity Model (SCCM) include

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- aiding smart city professionals in developing a long-term smart city vision and strategy,
- easing the management of multiple stakeholder interactions and digital technologies, and
- assessing potential dangers and costs

The ultimate goal of SCCM is to help remove barriers to the creation of creative business models and the creation of value inside smart city ecological systems while also empowering smart city stakeholders to better plan and assess smart city efforts. SCCM consists of the four main components, as well as the sub-components of strategy, technology, governance, and stakeholders. SCCM generates meaningful interrelationships between its various elements and subdivisions and offers a thorough framework for the design of smart city initiatives and environments [7,8].

Though there are many challenges to overcome, smart cities are increasingly turning to Big Data Analytics (BDA) to maximize their usage of existing infrastructure. Therefore, the primary purpose of this study is to examine the significant challenges that prevent BDA from being used to build smart cities [9,10]. To reach our objective, we first had to catalog the 13 roadblocks to BDA acceptance, and then we used the Best Worst Method (BWM) to rank them in order of importance. According to the results, three main factors are holding back the use of big data analytics (BDA) in creating connected cities: the intricate nature of the data, the need for a framework for using BDA, and appropriate technology. This research's most noteworthy contribution is its proposed technique for analyzing the barrier to BDA adoption associated with smart city growth. Regulators and managers may find the established method helpful in examining the barriers that prevent BDA adoption in smart city planning, design, and development. The study's findings can be used to facilitate the rapid growth of smart towns by removing these stumbling blocks. In order to provide better services to their citizens, smart cities are the subject of this research, namely how BDA can be included in their development. To this end, a systematic approach has been created to identify and prioritize the most critical barriers to implementing BDA. Two steps are used to determine the BDA barrier: a review of relevant literature and advice from subject matter experts. Once problems have been isolated, the BWM ranks them according to severity. The finding demonstrates that data difficulty, the lack of a framework for adopting BDA, the lack of technological solutions for BDA, and the lack of efficient processing platforms for massive volumes of data are significant challenges. Government officials and city planners invested in the innovative city development process should focus on overcoming these most pressing barriers [11,12,13,14].

Experts in sectors as varied as environmental protection, technological innovation, structural engineering, and others are being asked to weigh in on the selected criteria' relevance, reliability, and interconnectedness . After deciding on what dimensions and criteria will make up the hierarchy, the IF-AHP approach is used to assign weights to each. In conclusion, the emergence of smart cities is evaluated using the IF-DEMATEL method, which considers the relative importance of many factors in shaping this development. The proposed framework illustrates how smart living and governance, smart economy, and smart environment are the bedrock for the successful implementation of smart city efforts [15].

An investigation found that the outcomes of IF-AHP are frequently used to build immediate decisions by identifying the significance and priority of the parameters and criteria that affect smart city development . If the IF-DEMATEL results analyze the complex interdependencies between the parameters and requirements and classify them as causes and effects, the impact of making choices could be enhanced for a more extended period. This study provides a methodology for improving the performance of cities, particularly in developing nations, and its findings are similar to those of previous studies [16-18]. It also identifies preference dimensions and regions that can be used. This research aims to help policymakers by comparing the current situation to that of competitors and identifying the areas that need development to ensure longevity.

The rapid expansion of cities to satisfy the requirements of an ever-increasing population has resulted in various issues, including an increase in pollutants and congestion, an absence of sustained sustainability, and an effect on the natural environment. The idea of "smart cities," including "intelligent convergence systems," has been proposed as a potential solution to these issues. The concept of a "smart city," which would be based on communication, knowledge, and technology, arose to mitigate the adverse effects of industrialization. In light of this, a significant amount of effort has been put towards creating metropolitan areas that are more considerate of the environment and cleaner [19]. Still, there is a pressing need for extensive research into the difficulties associated with developing and evaluating intelligent cities in developing nations, particularly in

Africa. The only way to judge the success of such endeavors and the degree to which they were successful is through meticulous examination and contrast based on pre-existing criteria. As a result, this research aims to investigate and assess the most important aspects and requirements for SCD in the context of Morocco's intelligent cities. Let us hope that this study will assist us in reaching our objective.

2. Related Work. This article uses Nigeria's economy as an example to give a fuzzy-synthetic analysis of the obstacles to achieving the promised land of connected cities in developing countries. Defining and outlining the country's problems is a necessary first step toward establishing intelligent cities. The research adopted a method of deductive reasoning informed by progressive philosophy [20]. A planned survey was used to collect information from professionals in the built environment involved in delivering publicly funded buildings in Nigeria. Based on the previous research, we isolated and examined six problems associated with innovative city development. In addition to the issues of the economy, society, technology, and the environment, there are also governance-related issues. Cronbach's alpha was used to check for internal uniformity, the Shapiro-Wilks test to ensure data were normally distributed, the Kruskal-Wallis H-Test to ensure homogeneity and the Fuzzy synthetic assessment test was used to provide a holistic analysis of the challenges involved in becoming a smart city. It was determined that each of the six factors examined might significantly affect future smart city development in Nigeria. More specifically, environmental, technological, social, and legal difficulties are rising to the forefront. The adopted fuzzy synthetic approach provides clear and practical insight into the obstacles that must be overcome before the objective of building smart cities in underdeveloped nations can be realized. The present discussion on "smart municipalities" has paid less attention to Nigeria than it should have. This paper provides a solid theoretical foundation for future research on developing smart cities in developing countries, particularly in Africa, where conditions are similar to those observed here because it lays a solid theoretical groundwork for further study [21]. According to the study's conclusions, the country has much more important issues to deal with before it can even begin to explore the potential of urban renewal. High development, rapid population expansion, poor infrastructure, impoverishment, insufficient laws and rules, financial turmoil, and weak administration are the only issues plaguing today's world. Therefore, the results are instructive for the government and other stakeholders accountable for the city's development and the issues that must be resolved. This is an essential factor for politicians to consider if they care about fostering social equality for their constituents [22,23].

However, despite these limitations, the study still provides essential insights into the challenges involved in innovative city development. The strategy employed is what matters most. A mixed-method approach, beginning with the Delphi methodology to assess the difficulties identified in the primary literature and then moving on to extra statistical assessment techniques, may prove useful in future studies[24]. This will facilitate a more nuanced understanding of the challenges connected with smart city growth. One of the essential things that can be done to increase social responsibility is to integrate social, economic, and ecological perspectives. One of the most commonly claimed goals of smart city activities is to improve the standard of living of local citizens. By expanding the SCCM to include social and political factors, we may create smart cities that are both resilient and sustainable. Indicators that can be utilized to measure and assess the various smart city activities are also highlighted to aid in the management of innovative city initiatives and guarantee their achievement [25,26].

This research was undertaken to contribute to the continuing conversations about planning's place in the development of smart cities, make the argument for rethinking the tech-centric definition of a smart city, and give city planning a more prominent voice. The key dispute is that integrating city planning with three types of technology and science can significantly benefit residents. Examples of such fields include Big Data, spatial information systems, and Data Science. These three areas are coalescing into what is being called "Geospatial Artificial Intelligence." Here are the two broad policy objectives: to 1) make city services and operations more efficient and 2) raise everyone's standard of living [27].

The paper also defines a focused on people theoretical structure that shows how interdisciplinary collaboration between urban planning and the three technological-scientific domains can improve management practices and achieve smart-city policy objectives. Our research methodology will include an in-depth analysis of the current research on the topic. The paper reviews the exciting developments that have recently occurred at the crossroads of urban development and geo-artificial information. Also, it highlights the challenges that prevent geo-artificial intellect from successfully integrating into intelligent cities' creation, construction, and supervision. This study argues for reconsidering the smart city from an angle with a lower emphasis on technology to add to the continuing conversation about intelligent city construction in the modern era. We are going to finish the article having accomplished both of these goals [28,29].

In order to achieve the four overarching policy objectives, this paper proposes a people-centric framework for the bright city concept that leverages collaboration between urban planning and the academic fields of Big Data, Geographic Information Technology and Systems, and Data Science to form a new discipline known as Geospatial Artificial Intelligence (GeoAI): Objectives include, but are not restricted to 1) improving the quality of life for all city residents; 2) enhancing the effectiveness of urban services and operates; 3) addressing the critical social, environmentally friendly, and financial problems that threaten to destabilize urban systems at all scales; and 4) contributing to the creation of geographic information, data, and expertise on human-environment behavior. This article lays the groundwork for a new understanding of knowledgeable urban development by demonstrating how our proposed human-centric, GeoAI-enabled city-building structure can address not only the technical-instrumental challenges but also the socio-political, normative, and ethical concerns that currently and in the future plague urban areas [30].

There are two points here that should be kept in mind. The suggested structure is based on the idea that planners should have a more significant hand in designing, constructing, and administrating future intelligent cities, which will be run in part or entirely by distributed computer systems and ingrained digital sensors and actuators. Intelligent towns' development, design, and oversight can incorporate human aspects, collaborative leadership, and contextually aware criteria. When assessing the smart-city agenda's short- and long-term effects on the economy, environment, society, and built environment, planners are in a prime position to take a holistic view [31]. Our position is that planning should play a substantial role in implementing GeoAI and other smart-city technologies to safeguard the public interest and the needs of marginalized communities. Although we share these beliefs, we recognize that other academics may disagree and that the future role of architects in smart cities is still an open subject [32].

Furthermore, designers have historically played a significant role in various corporate and public spheres; nevertheless, other disciplines may eventually dominate these sectors. Second, many scholars have worked tirelessly over the past decade to close the gap between planning for cities and urban design (design-based, mechanical organizing) and the policy-based, socioeconomic planning commonly known as urban planning. The disciplines of city planning and urban design are vastly different. Additionally, the growth of zoning reforms, particularly the rising acceptance of form-based code, has created new circumstances to reconcile the design-oriented and policy-based realms of planning. The advent of form-based code and the development of zoning reforms contributed to this possibility. Motivated by these changes, this paper proposes a new paradigm for urban planning as a profession that combines urban design and urban planning. The document also offers a comprehensive strategy for future development. Still, we are realistic about how difficult it will be to achieve the necessary level of regional cohesion. Planners can come from a wide range of educational and occupational backgrounds, and their career goals and foci of study reflect this diversity. Planning experts may also view the built environment from different perspectives. We also believe that the confluence of planning many practices and research activities can be aided by establishing a clear vision and well-defined policy goals. The study's four policy goals stimulate cross-disciplinary cooperation and apply to various planning specializations.

It is clear from the research projects described in the study that GeoAI has opened up vast opportunities for collaboration between professionals and researchers in the field and between urban planners and researchers from other disciplines. Future studies may try to ascertain whether or not the use of GeoAI will influence the precision with which plans are executed[33].

The paper demonstrates how GIScience could methodologically and theoretically shape a GeoAI-based approach to planning, building, and managing intelligent cities through several analytical and practical examples. The concept of "smart cities" is a backdrop for these illustrations. For instance, our findings suggest that Critical GIS may enhance any GeoAI-based analytical framework focusing on smart cities. This is because Critical GIS promotes equity and social justice as the fundamental values of future smart cities by providing novel socio-spatial and technical tools for better visualizing spaces of flow, association, and network (Batty, 2013a). In addition, the article elucidates the challenges that smart cities face while trying to use GIScience solutions.

For instance, the potential for GeoDesign to function as an effective planning support tool in the context of smart cities was proven in Section 3. GeoDesign not only paves the way for a straight, concerted city planning framework to tackle multifaceted planning tasks with communities but also provides a platform for meaningful civic engagement and deep public participation. It helps to address acute challenges that will face cities in the future, such as interchange congestion and air pollution. However, we recognize that the success of GeoDesign depends on a vast number of parameters, much like the success of any other SDSS product. Factors including public confidence in planning authorities, local expertise in relevant fields, and institutional and organizational hurdles play a role. These and other variables can make it hard to use organizational aids effectively in the actual world [34].

This research also suggests several future lines of examination at the crossroads of developed city preparation, GeoAI, and Big Data, such as how government agencies can use geospatial AI to find health disparities, evaluate community requirements, distribute resources equitably, or predict economic classes. Shifts like development in communities while safeguarding the desires of the most marginalized residents? To reduce the overall building costs related to reasonable housing while expanding its beneficial financial and social consequences, how could SDSS methods maximize growth rewards and funding processes and discover properties ideal for housing construction. How can local transportation organizations use GeoAI's features to plan a multi-modal transportation network that accomplishes objectives like decreasing carbon footprints while increasing the availability of dwellings, amenities, and employment possibilities? How can we use the SDSS to locate ecologically fragile regions and human communities at risk from global warming? How can city planners prepare for recovery following a disaster and the possible relocation of sensitive neighborhoods? How can they build scenarios to lessen the impact of disasters? Because it is based on a literature review, the number of obstacles that can be identified is limited. The procedure has this downside. Prioritization is based on the expert's input, which might be biased depending on the expert's working level and can come from various disciplines. It is also possible to use fuzzy and grey theories to deal with the partiality of expert input, which is one of the drawbacks of research. Including instances from developing countries would significantly increase the reach of this inquiry. Future work may use Interpretative Structural Modelling (ISM) or Integrated Structural Modelling (TISM). Future studies could explore the observed barriers by employing various multicriteria decision-making (MCDM) techniques, such as the Base Criteria Method (BCM), CoCoSo, or others. The results of this research are expected to help people better understand the BDA barriers in modern urban areas.

In the case we have been given, the IF-AHP is used to analyze the problem's structure and to calculate the scores of the quantitative and qualitative dimensions/criteria using the ambiguous values provided by the experts. Later on, MCDM employs IF-DEMATEL to build the structural relationship among measurements and criteria. Intuitionistic fuzzy set theory helps deal with the vagueness of human language and the uncertainty of expert opinion. The results suggest that 'Smart Living and Governance' and 'Smart Economy' significantly influence SCD in Morocco.

The proposed approach prioritizes improving intelligent cities' decision-making capacities by understanding the dimensions/criteria and situations that distinguish smart cities from conventional ones. The managerial ramifications, results, findings, constraints, and potential future applications are also discussed.

The primary goal of this research is to examine the most critical factors and aspects that affect smart city development projects in poor nations, focusing on the Moroccan context. A novel framework employing the IF-AHP and IF-DEMATEL approaches has been created for this purpose. First, we conduct a comprehensive literature review and document review on creating smart cities to collect the most important criteria.

3. Research Methodology. Elements of fuzzy ISM and DEMATEL are combined into the approach that is discussed in this research. It is good knowing that the ISM and DEMATEL approaches are both powerful and valuable instruments that facilitate the process of decision-making. In order to convert the contextual link between variables into a hierarchical and fundamental model, the ISM technique takes an interpretive and iterative approach. If researchers want a deeper understanding of how the variables interact with one another, they could consult the structural model. The fuzzy information support model (ISM) was chosen for this investigation because it makes more efficient use of the subjective aspects of expert judgment. In addition, based on fuzzy logic, the ISM technique provides flexibility for the expert's preliminary evaluation to be adjusted and improved.

The direction of the link between complicated variables has been better understood with the help of fuzzy DEMATEL approaches. This investigation uses both fuzzy ISM and fuzzy DEMATEL in its methodology. This method makes it possible to investigate cause-and-effect relationships to shed light on the intricate dynamic between the various decision-making factors. A few case studies have been conducted to evaluate the novel combination of ISM and DEMATEL techniques. Both fuzzy ISM and DEMATEL can classify decision factors according to their driving and reliance power.

In contrast, fuzzy DEMATEL can also classify decision elements according to their predominance and connection. Using these strategies, the complex relationship can be uncovered even in an area with much mist. Even though it is successful at building a causal model between the many components of the system, the Fuzzy Integrated Systems Model (FISM) has some drawbacks in that it cannot quantify the strength of the links between the various components of the system. The DEMATEL methodology makes it possible to do statistical research on links. In order to obtain information that is useful, this study employs an approach that is a combination of fuzzy ISM and fuzzy DEMATEL. Figure 1 visually represents the study design's three distinct stages.

Phase I. Difficulties to implementing Big Data in smart city initiatives are identified and validated. At this point, we have used a method that incorporates both previous research and the insights of subject matter experts.

Phase II. Examining how the various obstacles to implementing Big Data in smart city initiatives are interconnected. First, the fuzzy ISM-MICMAC method is used to explore the historical interaction among the major issues, and then, based on their driving and dependent powers, these difficulties are sorted into several categories.

Phase III. Classification of the problems found. In this step, the link of causality between the complicated issues is analysed via a chart, using the fuzzy DEMATEL technique. Furthermore, difficulties are sorted into a reason and impact category based on the prominence and effect score. Administrators will benefit from this classification when developing an approach to fully exploit Big Data's potential applications in smart cities.

By holding a workshop to develop solutions to problems identified in the literature, this research makes the most of the participants' varied areas of knowledge. Later, in fuzzy DEMATEL, experts aimed to construct a contextual link in order to evaluate the difficulties differently based on the relative importance of each. A total of eight professionals with extensive experience managing Big Data and smart cities initiatives took part in this exercise. The following section will elaborate on the fuzzy ISM and fuzzy DEMATEL approaches.

4. Proposed Methodology.

4.1. Building Structures using Fuzzy Interpretation. The ISM method is widely used for modeling and categorizing interdependencies between different parts. Integrated system simulation, or ISM, creates a holistic, systematic model from a set of constituent pieces that are conceptually distinct but operationally interdependent. ISM considers the connections between parts of a system while creating a model. This method converts abstract ideas about a system into a concrete, hierarchical model that may be easily understood. The fundamental understanding of fuzzy inference and support mechanisms (ISM) uses several people's knowledge to construct a multifaceted model. It was implemented in earnest in the 1970s. Many researchers have used this instrument during their soft modeling investigation of intelligent businesses. Researchers provided a grading and value system based on a scale from 0 to 1, with 0.1 indicating fragile interaction dominance, 0.9 indicating extreme dominance, and 0.5 indicating a medium degree of domination. This was done using the Fuzzy ISM method in mind. Only a robust correlation will be considered, as measured by this metric. Fuzzy ISM adds value because it helps decision-makers focus on what matters. Here is a rundown of the broad procedures utilized in Fuzzy ISM in figure 4.1.

In the first step of the process, a conceptual self-interaction matrix, also known as an SSIM, is created by investigating the underlying connections between the previously obtained issues from the research. Second, we develop an initial reachability matrix based on the SSIM by employing this binary representation of the language signs. The third phase in the process involves the generation of a final accessibility matrix once it has been established whether or not the initial matrix of reachability had any bidirectional interactions. In the process's fourth step, the final reachability matrix is converted into a fuzzy reachability matrix by determining which relationships are the most dominating. Step 5 involves classifying the barriers according to their levels

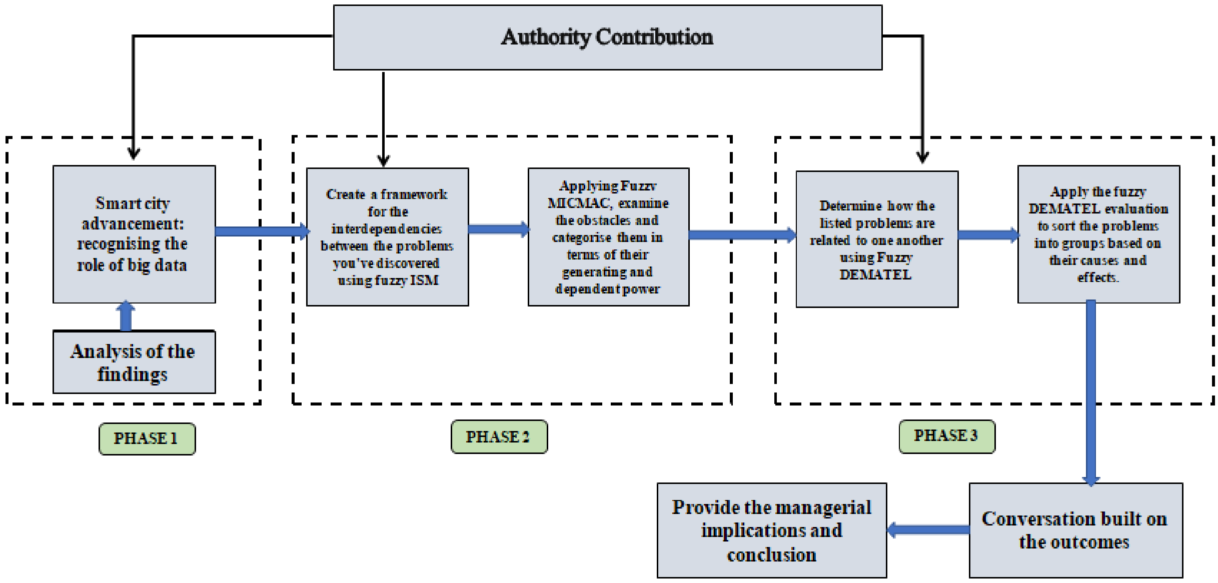

Fig. 4.1: Study design and rationale provided

of complexity. The sixth phase is creating the Fuzzy ISM model by classifying the challenges encountered. The newly developed Fuzzy ISM model is subjected to a thorough examination in Step 7 to identify and correct any theoretical errors.

4.2. Fuzzy DEMATEL. Between 1972 and 1976, researchers at the Battelle Memorial Institute's Geneva center developed a device called DEMATEL. This technique uses a causal graph to investigate the interconnections between the various parts. This strategy is often used to examine the connections between the many factors in reaching a choice. The authors used this technique to analyze the impact of the Internet of Things on the supply chain, evaluate the barriers to sustainable end-of-life practices, analyze the external barriers to refurbishment, benchmark the implementation of logistics management, and evaluate strategies to reduce the risk of sewer exfiltration. This strategy was used to accomplish all of these goals. The simulation allowed the researchers to examine the connections between the many obstacles to environmentally responsible supply chain management in the leather sector. The fuzzy DEMATEL model was also used to examine the challenges of getting Halal certification. The subjective character of the specialist's inputs led to an analysis that, in some places, reached a result that needed to be more transparent and correct. The fuzzy set theory provides a powerful tool to deal with uncertainty and imprecision. It gets its name from the inherent fuzziness of the underlying notion. Therefore, we combine the more conventional methods of ISM and DEMATEL with the fuzzy number to use the qualities that a fuzzy number gives. Triangular fuzzy numbers, trapezoidal fuzzy numbers, or both are commonly combined with MCDM techniques. Due to their computational simplicity, Triangular Fuzzy Numbers (TFNs) will be incorporated into this investigation alongside the DEMATEL. Breaking down the fuzzy-DEMATEL method into its parts yields the following.

Step 1. Build a matrix to determine what factors should be considered when evaluating language skills.

The expert's input is utilized to establish a five-point linguistic scale that is then used to create an assessment matrix of linguistic influence. Each expert had to weigh the significance of a single element against that of others (in this example, each barrier). In this statement, a_{ij} stands for "factor x greater than factor y". In the straight inflectional matrix, the values of the diagonal elements are all zero (that is, 0, 0, 0). It is possible to receive a non-negative n3n matrix from a single expert in the form of $A^k = [a^k_{xy}]$. In this way, we gather H matrices from H specialists in the field, with indices $A^1, A^2, A^3, \cdots, A^H$.

Step 2. Discover what matrix (A) represents the initial fuzzy direct relations.

Applying the three-dimensional (x, y, z) representation of the TFNs, we can calculate the fuzzy initial direct connection matrix $L = [b_{ij}]_{t\times t}$ using Equation 4.1, which we then use to do the linguistic evaluation.

$$b_{ij} = \frac{\sum_{k=1}^{H} a_{ij}^{k}}{H} \tag{4.1}$$

where "H" indicates the overall amount of expertise and "a_{ij}^{k}" represents the weight given to "i" by "j" in the opinion of the kth expert, "i" and "j" are both considered in the formula. Matrix "L" is unsuitable for matrix operations since its elements are fuzzy numbers. As a result, there is a need to convert hazy figures into more precise ones. Matrix operations require these fuzzy numbers to be defuzzed. For the purpose of defuzzification in this research, we use Equation 4.2 and the weighted average technique.

$$a_{ij}^{k} = \frac{1}{6}(s + 4t + u) \tag{4.2}$$

Step 3. Acquired the basic direct-relation matrix and normalised it to N.

$$[M]_{n\times n} = T \times [X]_{n\times n} \tag{4.3}$$

$$\text{where } T = min[\frac{1}{max \sum_{j=1}^{n} |x_{ij}|}, \frac{1}{max \sum_{i=1}^{n} |x_{ij}|}] \tag{4.4}$$

The [N]-by-[N] matrix, where every component's result is between 0 and 1.

Step 4. Utilise the entire Connection Matrix "R" Calculation in Equation 4.5.

$$[R] = [N][I - N]^{-1} \tag{4.5}$$

The identity matrix is denoted by "I" here.

Step 5. Equations 4.6 and 4.7 are used to determine the causative variables:

$$K = (c_i)_{n\times 1}[\sum_{i=1}^{n} t_{ij}]_{n\times 1}\forall_j \tag{4.6}$$

$$L = (d_i)_{1\times n}[\sum_{j=1}^{n} t_{ij}]_{1\times n}\forall_i \tag{4.7}$$

where "c_i" is the element-sum of the ith row of the matrix [R], and "i" is the factor whose influence (direct and/or indirect) is being measured. Similarly, the total effect (direct and indirect) that factor j got from the other factors is represented by d_j, which is the sum of the components in the j^{th} columns of the matrix [R].

Step 6. The significance (D_i) and neutral influence (F_i) rating are used to create a causal diagram. These ratings are determined by plugging values into Equations 4.8 and 4.9.

$$D_i = r_i + c_j|_{i=j} \tag{4.8}$$

$$F_i = r_i - c_j|_{i=j} \tag{4.9}$$

The significance of the degree of factor i is illustrated by the "$r_i + c_j$" phrase. The "$r_i - c_j$" word, on the other hand, illustrated the overall impact; the value added by element i. The value of "$r_i - c_j$" also determines where a given causal component falls inside a given effect group. If "$r_i - c_j$" is positive, then the component is part of the cause group; otherwise, it is part of the effect group.

5. Experimentation and Results.

5.1. Examination of Big Data difficulties in creating smart cities. In this piece, we'll dissect the intricate web of interdependencies that arise from using Big Data to build smart cities.

5.2. Implications of Big Data's Uncertainty in Fuzzy ISM Simulation for Smart City Growth:. The subsequent portions represent the discovered difficulties associated with using Big Data in the creation of smart cities according to the stages of fuzzy ISM approaches.

1. Correlation between problems in circumstances. First, with the aid of expert opinion in an idea engineering workshop, a conceptual correlation is formed between the highlighted difficulties through pairwise comparisons. L, M, N and O signs are utilised to complete the alphabetic SSIM, where

L- Both (i) and (j) are affected by (i), but not vice versa;

M- Both (i) and (j) are affected by (i), but not vice versa;

N- The (i) and (j) challenges are bidirectional challenges;

O- Problems (i) and (j) stand alone, unrelated to one another.

2. A matrix of possible actions in a fuzzy system is created. The SSIM matrix is subsequently transformed into a matrix consisting only of 0s and 1s; this matrix is called the initial accessibility matrix. The following are the guidelines for constructing the initial accessibility matrix.

a.If the value in cell (i, j) is V, then the value in cell (i, j) is 1, and the value in cell (j, i) is 0;

b.if the value in cell (i, j) is O, then the value in cell (i, j) is 0, and the value in cell (j, i) is 0;

c.if the (i, j) cell is X, then (i, j) = 1 and (j, i) = 1;

d.if the (i, j) cell is A, then (i, j) = 0 and (j, i) = 1;

e.if the (i, j) cell is Y, then (i, j) = 0 and (j, i) = 1;

It displays the results of this conversion to a fuzzy accessibility matrix, which takes into account the dominance of the links among difficulties. The strength and interdependence of different obstacles can be calculated by adding up the rows and columns of the fuzzy accessibility matrix.

3. Classification by level. In this stage, three sets are built using the final accessibility matrix: the reachability set, the antecedent set, and the intersection set. The range of difficulties that can be achieved includes the work at hand and any tasks inspired by it. The initial set includes not only the difficulties themselves but all the factors driving that task. Neither the accessibility set nor the initial set includes the problems unique to the intersection set. When a task's reachability set and intersection set yield identical results, the problem is classified as Level I and taken out of further iteration consideration. The data gleaned from this test was then used to shape the design of the subsequent levels.

Each iteration comes with varying difficulties, each tailored to a specific challenge.

Once the initial eight iterations have been completed, difficulty levels are assigned to each task, and the digraph is built by placing the tasks in the proper levels. The challenges of the first level can be found at the very top of the digraph. As the digraph's hierarchy decreases, the level number rises in tandem with it. The digraph is shown here in its transformed state as a hierarchical and structural model.

In line with the leveling, the fuzzy ISM model provides evidence of relative importance. All the other problems that arise when using Big Data to build intelligent cities stem from the two underlying difficulties, "Smart City diverse population" and "Technologies for Big Data and infrastructure faults," located at the bottom of the framework. The "Information intricacy" problem has progressed to the second level of the model's architecture. Level 1 problems, which include "Data Planning and Analytical Challenges" and "Information Interpreting Problems," have little impact on the model. All the other variables in the model serve as drivers for these. Its ability to motivate and rely on others is a sign that it is deeply intertwined with other problems.

The results of fuzzy ISM show how problems with innovation can impede the evaluation of enormous data sets and give rise to new challenges. Therefore, to mitigate the impact of other challenges, it is necessary to employ error-free systems and architecture.

5.3. MICMAC analysis. MICMAC is an abbreviation for "Matriced'Impacts cruises-multiplication applique," which means "cross-impact matrix multiplication used for categorization." Here, we use MICMAC to study the 14 tests that went into establishing the ISM model. According to Haleem and Khan (2017), the MICMAC analysis is performed to ascertain how much of a driving and dependent power the issues in a system

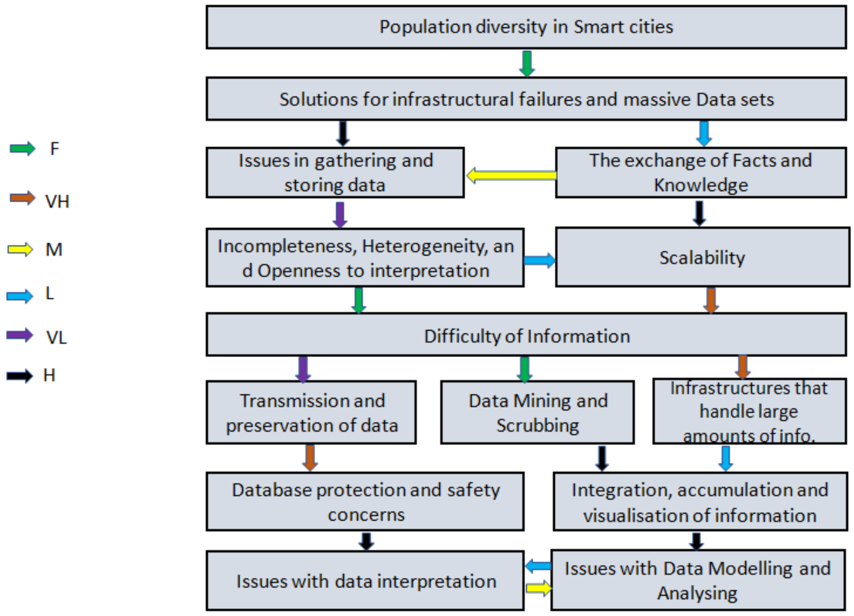

Fig. 5.1: Big Data problems in smart city development using a Fuzzy ISM-based model

have. See Figure 5.1 for a visual representation of this concept. In a two-dimensional in-nature rectangular plane, the dependence power is plotted along the abscess and the power that drives along the ordinate. Here, the impetus comes from a string that spans all pertinent challenges in figure 5.1.

Similarly, the sum of the ones in each column stands for the reliance on strength. The degree to which a difficulty can be overcome indicates its potential as a motivating factor. Reliance Power is a similar metric that assesses the impact of additional issues on the central ones. We have identified the root causes of all fourteen problems and established their interconnectedness. In addition, the challenges are partitioned into four distinct groups using this method. In the Table, we will see the results of the MICMAC inquiry.

5.4. Fuzzy DEMATEL analysis. This subsection will determine, through the use of the fuzzy DEMATEL methodology, the nature of the causal relationship among the aforementioned challenges that Big Data poses to the development of smart cities. The professionals evaluated the issues by placing each issue on a scale according to how important it was in comparison to the other issues using a language scale. An individual matrix is generated as a result of the responses provided by the specialists. After that, these matrices are transformed into a fuzzy connection matrix through the application of the triangular fuzzy number. In addition, the responses of the specialists are combined to produce the Overall Direct- Relationship Matrix, denoted by the letter A. In a later stage, the standardized direct-relationship matrix, which is denoted by T and is derived by applying Equations 4.3 and 4.4 is obtained.

Figure 5.2 depicts the 2-dimensional rectangle surface used in MICMAC analysis, with the dependent energy on the circumference and the motor force on the centre point. Here, the impetus comes from the total number of ones in the column for all the relevant tests. Similarly, the dependency strength is the total number of ones in the tables.

After that, the total relationship matrix (T) for each obstruction is computed by using Equation 5, together with Equations 4.6 and 4.7.

The total relation matrix (T) is then used to determine the sum of each row and column, which is then stated by the variables K and L in the appropriate manner. Ri is a representation of the overall effect that the difficulty has had on the other difficulties, and Cj is a representation of the net influence that the subsequent difficulties have had on the previous difficulties. Following the determination of the values of R and C for each

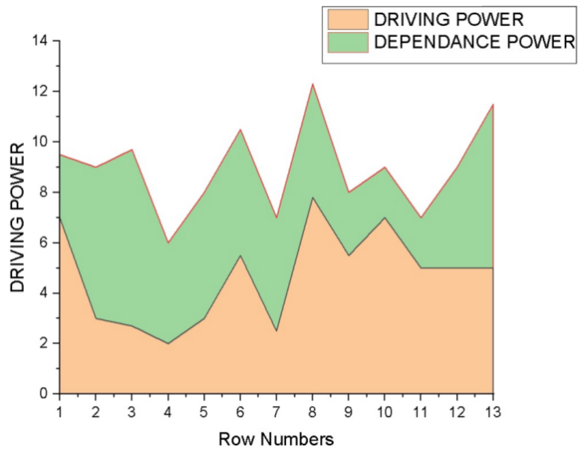

Fig. 5.2: Reliance diagram for difficult situations

row and column, Equations 4.8 and 4.9 are applied in order to compute the prominence (Di) and the net effect (Fi). The ultimate cause and consequence of each test are both decided by "Di." If Di is in a favorable position, then it is thought that the challenge will produce the net cause; however, if Fi is in an unfavorable position, it is thought that the challenge will produce the net impact. Table 12 illustrates the association that exists between the two variables. The K and L values, which also reflect the natural effect that each challenge has on the system, are used to determine the importance order of the challenges. This order is based on the K and L values.

The importance of the ranking of the challenges presented by Big Data for the development of smart cities has been calculated as follows, based on the "prominence" value: Data Organisation and Mobility Problems (13) > Big Data Computing Systems Problems (7) > Interpreting the Data (12) > Data visualization and Assessment (11) > Data incorporating, Grouping, and displaying (10) > Data Collection and Capturing (8) > Data Collecting and Grabbing (Knowledge Retrieval and Elimination (Similarly, the challenges are classified according to their "effect" values) The level of complexity (K L). With reference to the diagram of causes and effects, the following are the most critical challenges, listed in descending order of the influence they have on the situation: Smart City population variety (6) > solutions for large information and infrastructure faults (3) > heterogeneous surroundings, discrepancy, and adaptability (4) > performance, availability, and longevity (5) > knowledge and data exchange (2) > data collecting and recording (8). In a similar vein, the difficulties that are being impacted by this factor are mentioned below in ascending order: Data visualization and evaluation (11) > Interpretation of information (12) > Data safety and confidentiality (1) > Data swapping, gathering, and representation (10) > Storage space of data and Shipping Problems (13) > Obtaining data and disinfection (9) > Big Data Recognising Systems Concerns (7) > Data challenges (14). The data gathered in this manner were presented to a panel of industry professionals in order to gain further insight, which will be detailed in the next section.

5.5. Discussions on results. Big Data is essential in planning and evaluating cities' amenities, including traffic control, medical care, schooling, security for the public, and visitor attractions. The implementation of big data serves as a potent decision-making tool by delivering reliable data and lowering the operational expenses of administration. According to the study's findings, the "Diverse inhabitants of Smart cities" is the most critical obstacle that must be overcome before Big Data can be effectively applied to creating an intelligent environment. According to Osman (2019), having an array of people and an extensive population contribute significantly to the volume and variety of collected data. The programs that use big data must continue to move in the appropriate direction to address the problems that threaten the sustainable development of communities. The next set of difficulties will require considerable expenditures in both equipment and software to support the analysis of tens of millions of recordings in real-time. One of these issues will be ensuring the creation

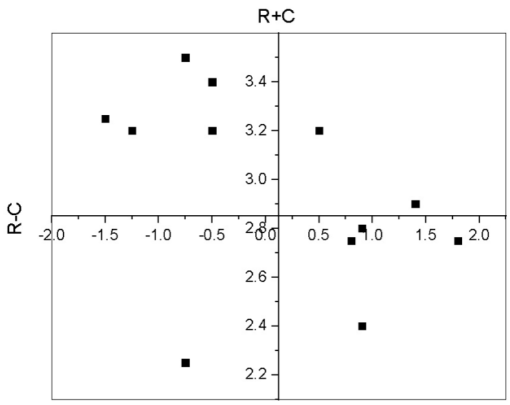

Fig. 5.3: Growth in smart cities and the difficulties of using big data: a cause and effect diagram

of methods for Big Data analytics, including the detection of infrastructural problems. The findings of this research are backed by prior research that looked at how big data could be used in the construction of smart cities. According to Al Nuaimi et al. (2015), the inhabitants of a city affect Big Data applications because the amount of data will expand and might grow extremely large. According to Khan et al. (2017), for a Big Data application to be practical, it must integrate the many city agencies responsible for arranging for and taking care of assets consumption in figure 5.3.

However, transferring information and facts between departments is challenging because every division maintains its confidential data, which they are hesitant to divulge to other departments. In addition, difficulties arise when attempting to share information with other organizations due to privacy concerns connected to the gathering and utilization of data. A significant quantity of data is collected from various locations; most of this data can be processed and compacted without jeopardizing the primary purpose of data collection. Due to the massive nature of Big Data, which makes it challenging to store in its entirety, its contents should be filtered so that it does not throw away any of the details.

Data collection presents a considerable problem since data are frequently time- and space-connected, requiring great care. Protecting one's safety and confidentiality in a smart city that uses Big Data is a significant concern. It is essential to prevent improper utilization of data that may contain sensitive or private data, such as that which relates to the actions of individuals or the authorities' decisions. According to Rathore et al. (2018), organizations that are in charge of offering a variety of smart services are required to implement a high-security standard across the entire network. In the context of a smart city, "Big Data" refers to documents such as financial information, health and medical records, and personal histories, all of which have the potential to provide detailed perspectives of the people they represent. The unauthorized use of this kind of data for the purpose of earning a profit violates the privacy of citizens. In smart cities powered by Big Data, one of the most significant challenges is the implementation of rules that protect the inhabitants' right to personal privacy. In a similar vein, Zoonen (2016) stated that data-driven city services, despite the fact that they will make the city environment less polluted, more prosperous, and more environmentally friendly, will destroy the creativity and deviance of the people who live there, as well as the workers and visitors. It should come as no surprise that urban Big Data plays a vital part in fostering wellness and ensuring the continuation of equitable growth. In opposition to the more conventional strategy of storing data first and processing it afterward, real-time data analytics is becoming a steadily significant tool. On the other hand, in order to get insights from the data in real-time, innovative methods and presentation approaches are required.

In addition, the present-time data analysis calls for a powerful Big Data processing infrastructure equipped with enormous processing and computing capacity. Software systems need to be secure, dependable, and error-tolerant for extremely heavily data-driven usage. A new media for storage is required because of the proliferation of data coming from various sources in a smart city ecosystem.

Another one of the challenges involves moving the data from its storage location to the platform where it will be processed. Analyzing data in real-time and conveying knowledge of relevance are necessary steps in this process. Collaboration, accumulation, and depiction of numerous sources as erroneous, lacking, and using the proper format constitutes another critical challenge that needs to be handled. This obstacle must be overcome. The facts that must be made decisions cannot be revealed by the data. The statistical analysis of big data arrives at the inherently complicated problems of being complex and messy. It is only possible to derive reliable details from urban data by managing the data quality. Since data gathering in a smart city ecosystem relies on crowd funding, digital information is stored in different independent databases with distinctive file types. This is because inaccuracy and disparity issues impair the decision-making process's potential. Big data is being utilized to improve the delivery of services in today's cities, which are also referred to as equitable, inclusive, and resilient towns in contemporary writing. The use of available resources will be maximized if a comprehensive and dependable plan is developed to address the issues of integrating Big Data applications within a smart city context.

6. Conclusion. Through fuzzy information systems modeling (ISM), the challenges posed by Big Data in developing smart cities have been explored and examined. It has been determined that "Smart City diversified demographic" and "Technologies for Big Data and infrastructural problems" are key obstacles and that resolving these problems can alleviate a great deal of the problems that have been identified. Participants can use the methodology in this article to better comprehend the challenges related to Big Data's inclusion in smart urban growth. For the establishment of smart towns to move forward beyond hindrance and at more incredible speed, it is helpful to solve these obstacles in an ideal manner; doing so requires a deeper view of how these challenges interact with each other using DEMATEL's fuzzy logic.With the proper handling and evaluation of the Big Data produced in smart cities, many of the current challenges experienced by smart cities might be avoided, allowing for their widespread acceptance.Constraints include 14 culminating obstacles, increasing the likelihood that specific critical actions will not be completed.

The specialists' inputs, which come from many various areas of study, are highly subjective, and this poses a severe problem. Both the ISM and DEMATEL provide a picture of the interplay between Big Data problems in the context of developing countries. Some identified problems may have the most significant impact in the here and now, but as technologies develop, those advantages may wane or become obsolete. Future research can use the modeling of structural equations to test and refine the fuzzy ISM-based hierarchical model. In addition, several decision-making frameworks can be used to investigate the identified issues. Case studies that map challenges with potential solutions provide a means of digging further into the research's findings. The highlighted challenges that can be a barrier for smart cities can be detailed by examining the various categories that can benefit smart city entrepreneurs and officials. It is hoped that this study will help fill in some gaps in our understanding of the challenges Big Data presents to the growth of smart cities and the integration of both the public and private spheres.

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