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Article

A Fuzzy Governance Model For E-Governance

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Abstract: Fuzzy mathematics offers a robust approach for handling uncertainty and vagueness in real-world problems, where conventional binary logic or exact mathematical methods are insufficient. Applications of fuzzy mathematics are found in many areas like- **control systems, pattern recognition, decision making, expert systems, robotics, financial analysis, medical diagnosis, etc**. Again, e-governance seeks to utilize technology to reshape government operations and engagements with citizens, fostering increased efficiency, transparency, and responsiveness within governance procedures. In recent times, the Fuzzy Governance Model applicable for corporate governance has also been proposed. This paper aims to check whether the Fuzzy Governance Model proposed by Enriqueta Mancilla-Rendon et al. (2021) could be applied in the case of an e-governance scenario with minimal necessary changes. For this, we have proceeded in the light of the conceptual model of Bhuvana et al. (2022), named "Actual Usage Model for E-governance Health Care Applications", where *public trust*, *service quality* and *information quality* are considered as independent variables and *actual usage of e-governance health care applications* is considered as the dependent variable. We have concluded that the said model proposed by Enriqueta Mancilla-Rendon et al. could be applied to e-governance too. Here, it has also been noted that the managements of e-governance services should try to provide the services keeping the values of all the said attributes (independent variables) around the satisfactory levels as per the suggestions of the experts.
Keywords: Governance, e-Governance, Decision-Making, Fuzzy Logic, Fuzzy Governance Model.

MSC Classification: 03E72 . 03B52 . 93C42

1. Introduction

Governance [1] is the framework of procedures, systems, and methods used by organizations, institutions, or governments to make and carry out decisions, uphold accountability, and manage resources efficiently. It encompasses the tools and principles of decision-making, citizen involvement, openness, and rule enforcement. In a democratic setup, governance includes conducting fair elections, creating policies through elected officials, promoting transparency through laws like the Right to Information, and providing essential services via government departments. A practical example is the Mid-Day Meal Scheme in schools, which reflects governance through planned policy, administrative execution, and ongoing monitoring.

e-Governance [2] involves utilizing ICT in governmental operations to enhance governance. Essentially, it refers to the public sector's adoption of ICTs to enhance the delivery of information and services, promote citizen engagement in decision-making, and enhance government accountability, transparency, and efficiency.

Fuzzy set theory, introduced by Lotfi A. Zadeh [3] in 1965, expands traditional crisp set theory by allowing elements to belong to a set to different degrees rather than simply being classified as either fully included (1) or excluded (0). This idea makes it possible to represent uncertainty and vagueness more naturally, reflecting how people often think and make judgments in real life. Because of this flexibility, fuzzy set theory has found wide applications in areas such as control systems, artificial intelligence, and decision-making processes. *Fuzzy logic* could be employed to guide administrative or implementing agencies in prioritizing areas for enhanced effectiveness and success of e-governance projects. These initiatives are designed to streamline and improve governance processes. In such a way, Fuzzy mathematics offers a robust approach for handling uncertainty and vagueness in real-world problems where conventional binary logic or exact mathematical methods are insufficient.

We have a *Fuzzy Governance Model* proposed by Enriqueta Mancilla-Rendon, et al. (2021) [4], applicable in some cases of *corporate governance*. Their work demonstrates the interaction between inductive and deductive reasoning in implementing fuzzy models and the qualitative attributes outlined in organizational internal laws. It introduces a tool to assess the governance level of agents within corporate governance as a dynamic complex system.

Again, M. Bhuvana et al. (2022) [5] proposed a conceptual model named "Actual Usage Model for E-governance Health Care Applications (Rural Citizen-EGOV.HA-AU Model)". Here *public trust*, s*ervice quality* and i*nformation quality* are considered as independent variables and *actual usage of e-governance health care applications* is considered as the dependent variable in the model. Here, we have proposed to use this model with a bit modification, treating it as a generalized case and not restricted only for the health care applications.

This study explores the potential usefulness of a fuzzy governance model, rooted in fuzzy set theory and fuzzy logic, in an e-governance scenario for *decision-making* management. It underscores the utility of a fuzzy logic based model in evaluating the internal control policies necessary for enhancing success of a project in e-governance. Here, we are trying to check whether that model could also be used in case of e-governance with a little change, if necessary.

2. Literature Review

2.1 e-Governance

The term 'e-Governance', is really related to the area of public administration and not to the area of business administration. There is a fundamental difference between the basic approaches of the two and that is that public administration basically runs on the "first choice" approach, whereas business administration runs on the "best choice" approach. But the modern trend is to use the corporate houses' working style in the field of public administration also. So, the e-governance services are planned with "best choice" approach [2].

ICT applications influence the frameworks of public administration systems. Technological progress supports administrative systems by enabling [2]:

a) Administrative Development; and

b) Effective Service Delivery.

In summary, e-governance entails using ICT in government operations to achieve SMART governance [2], which stands for simple, moral, accountable, responsive, and transparent governance.

e-Governance involves utilizing information and communication technologies by governmental bodies, civil society, and political institutions to interact with citizens, fostering dialogue and gathering feedback to enhance citizen participation in the governance processes of these institutions. e-Government can be considered as a component of e-governance, primarily aiming to enhance administrative efficiency and mitigate administrative corruption [6].

The effectiveness of an e-governance initiative hinges on its comprehensive and unified development. It should not be limited to acquiring hardware and networking gear alone. e-governance represents the integration of diverse management domains, transforming it into a strategic management endeavor rather than just a technology-driven project [7].

2.2 National e-Governance Plan in India

The National e-Governance Plan (NeGP) [7] in India was formulated collaboratively by the Department of Information Technology (DIT) and the Department of Administrative Reforms and Public Grievances (DAR&PG). It was approved by the Union Government on May 18, 2006, and comprised 27 Mission Mode Projects (MMPs) along with eight supporting components. The government also endorsed the NeGP's overall vision, strategic approach, core elements, and implementation framework.

Given the multitude of agencies involved in implementing NeGP and the necessity for comprehensive aggregation and integration at the national level, NeGP is designed as a structured program with clearly defined roles and responsibilities for each participating agency. Therefore, establishing an appropriate program management framework is essential for the entire initiative [8].

2.3 Management of e-Governance Related Projects in India

Normally, in India, different committees at National Level, State Level, District Level, and Revenue Circle/ Development Block Level are formed as per requirements for implementing a e-governance related project. Also, some IT related organizations/ agencies are vested with the responsibility of looking after the technology related matters. For example, the management of the e-District project in Assam is assigned to a District e-Governance Society (DeGS). There were 27 DeGS operating across the state at the time of launching the project, each chaired by the respective District/ Deputy Commissioner. To oversee and manage the project's operation at the district level, an e-District Project Manager (eDPM) is appointed for each district. As part of the e-District project's implementation in Assam, the Assam Electronics Development Corporation Ltd. (AMTRON), a Public Sector Undertaking under the IT Department, has been designated as the State Designated Agency (SDA). In this role, AMTRON oversees the project across the entire state, ensuring comprehensive management and end-to-end execution in line with the defined scope and scheduled timelines [9].

2.4 Actual Usage Model For e-Governance Applications

M. Bhuvana et al. (2022) [5] proposed a conceptual model named “Actual Usage Model for E-governance Health Care Applications (Rural Citizen-EGOV.HA-AU Model)”. Here *public trust*, s*ervice quality* and i*nformation quality* are considered as independent variables and *actual usage of e-governance health care applications* is considered as the dependent variable in the model. We have proposed to use their model on “Actual Usage Model for E-governance Health Care Applications” by accepting it to be applicable for all e-governance services. A simple modification has been made in it and the modified model in given in *Figure 1*.

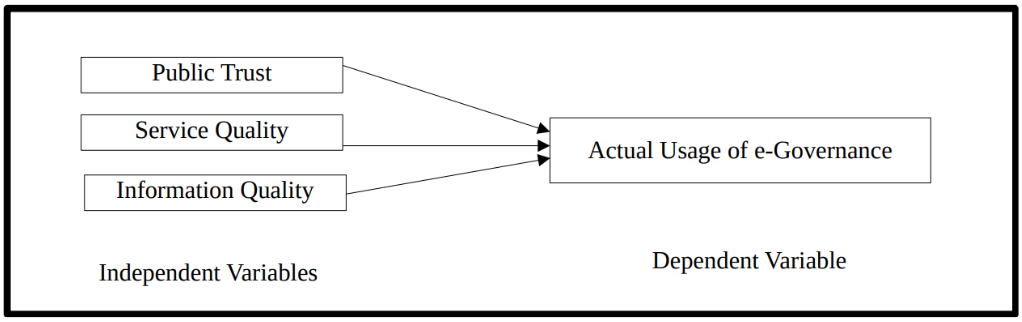

Figure 1: Actual Usage Model for e-Governance [5]

2.5 Fuzzy Governance Model

Enriqueta Mancilla-Rendón et al. (2021) [4] proposed a Fuzzy Governance Model for corporate governance. Their work demonstrates the interaction between inductive and deductive reasoning in implementing fuzzy models and the qualitative attributes outlined in organizational internal laws. It introduces a tool to assess the governance level of agents within corporate governance as a dynamic complex system. In many organizations, processes – especially undocumented ones – are frequently missing or insufficiently defined, and proper documentation for assessing policy compliance and internal control mechanisms is often lacking. In this context, fuzzy logic offers an innovative and effective approach for evaluating the level of compliance of processes, particularly when formal documentation is unavailable. Their proposed model is given in *Figure 2*.

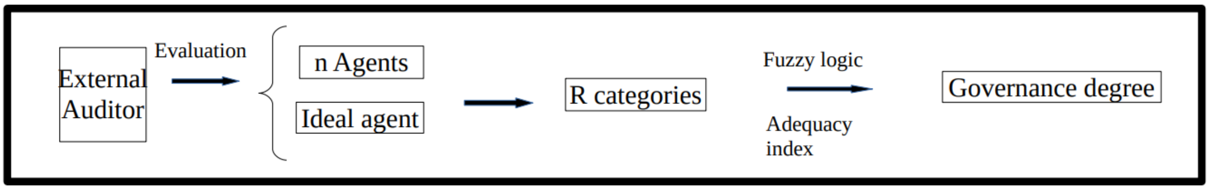

Figure 2: Governance Structure [4]

In the following paragraphs, we have made a review of the recent related studies made by different authors in twenty-two (22) numbers of different research papers:

Enriqueta Mancilla-Rendón et al. (2021) [4] analysed the roles of corporate governance agents as a critical aspect of the independent auditor's study and evaluation of internal control, ultimately proposing a governance fuzzy model grounded in legality. It employs a cross-sectional research design, using fuzzy logic theory as an alternative to traditional mathematical models. The scientific contribution of their work lies in demonstrating how the integration of fuzzy set theory-based mathematical models with the qualitative aspects of internal control policies and practices can serve as a tool for evaluating governance as a management system for decision-making. The study highlights the utility of a fuzzy set-based model in assessing internal control policies and procedures to enhance corporate governance.

M. Bhuvana et al. (2022) [5] proposed a conceptual model named “Actual Usage Model for E-governance Health Care Applications (Rural Citizen-EGOV.HA-AU Model)”. Here *public trust*, s*ervice quality* and i*nformation quality* are considered as independent variables and *actual usage of e-governance health care* *applications* is considered as the dependent variable in the model. We have proposed to use the above model in our case with a bit modification treating it as a generalized case and not restricted only for the health care applications.

Angel Cobo et al. (2014) [10] introduces a novel multi-criteria approach for assessing IT Governance (ITG) with a focus on Strategic Alignment. The assessment framework utilizes the Fuzzy Analytic Hierarchy Process (FAHP) and is tailored specifically for IT processes, especially those associated with COBIT© maturity levels, domains, and processes, enabling a detailed and refined evaluation of the relative significance of each component. Its significance lies in addressing the typically isolated and individual evaluation criteria often used in process audits. The model generates information that enhances compliance and corporate governance assurance across various organizations. The study highlights that combining multi-criteria decision-making methodologies with soft computing is especially effective in addressing strategic alignment, as emphasized in COBIT.

V R B Kurniawan et al. (2021) [11] presented a case study on evaluating supplier selection factors for a small-medium scale paper manufacturer in Indonesia, utilizing the fuzzy best-worst method (fuzzy BWM). They observed that the BWM method, which compares factors through the best and worst criteria with structural consistency, is enhanced with fuzzy logic to handle the uncertainty in decision-makers' judgments. The evaluation considers five supplier criteria: service, flexibility and delivery, reputation, quality, and purchasing cost. To compute the fuzzy weights of the criteria, a nonlinearly constrained optimization problem was formulated. The findings revealed that service was the most important criterion, while purchasing cost was the least important, with service being slightly less critical than quality. Additionally, the Fuzzy BWM provided a high level of consistency in the comparisons. The optimal weights determined in this study can be used to rank suppliers in future evaluations.

Geng Peng et al. (2021) [12] integrated fuzzy mathematics with the Analytic Hierarchy Process to assess risks related to land conflicts, effectively addressing uncertainty and imprecision in the evaluation process. Drawing on the underlying principles of land conflict risk assessment, they constructed a comprehensive index system using the fuzzy analytic hierarchy process (FAHP). The results revealed an overall moderate level of risk, with the feasibility and controllability indicators requiring particular attention. The study contributes in two major ways: first, it confirms the suitability of FAHP as a reliable tool for land conflict risk assessment; second, it offers practical insights to support governments in developing more rigorous safety and management strategies for land exploration conflicts based on the assessment outcomes.

Francesco Calza, et al. (2015) [13] observed that service systems facilitate value co-creation and are deemed "Smart" when supported by IT, allowing them to adapt to external changes to benefit the entire system. Value co-production occurs through processes that coordinate participants who exchange services, including decision-making activities like selecting a specific service provider. Governance plays a crucial role in decision-making, often balancing the expectations of all involved. In selecting service providers from a group of suitable candidates, a Fuzzy Consensus Model can be employed in a Group Decision Making (GDM) scenario within a service context. This model involves a set of Service Providers (as potential options) and decision-makers who evaluate these options to arrive at a consensus. The model incorporates fuzzy preference relations and an advice generation mechanism to assist decision-makers.

Jiuying Dong et al. (2021) [14] introduce a novel fuzzy Best-Worst Method (BWM) that utilizes triangular fuzzy numbers for multi-criteria decision-making (MCDM). This approach focuses on the best-to-others and others-to-worst vectors, represented as triangular fuzzy numbers, and treats consistency equations as fuzzy equations. The process of determining the optimal fuzzy weights for criteria is framed as a fuzzy decision-making problem, and a mathematical programming model is developed to derive these optimal fuzzy weights, resulting in a normalized triangular fuzzy weight vector. Furthermore, we present four linear programming models based on this mathematical model, tailored for optimistic, pessimistic, and neutral decision-makers. By appropriately selecting tolerance parameters, each linear programming model guarantees a unique global optimal solution. Additionally, they introduce the concepts of a fuzzy consistency index and a fuzzy consistency ratio. Several examples are provided to demonstrate the effectiveness of the proposed fuzzy BWM, highlighting its utility in MCDM within fuzzy environments.

Yan Liu et al. (2020) [15] review the Analytic Hierarchy Process and its fuzzy extension (FAHP), highlighting the need to address uncertainty in subjective pairwise comparisons. They note that although many FAHP methods exist, their relative advantages are rarely compared, making method selection unclear. Their study reviews post-2008 literature on fuzzy AHP applications in industrial decision-making, particularly selection problems, and classifies techniques based on representation, aggregation, defuzzification, and consistency assessment. It evaluates each method’s principles, strengths, and limitations, providing tables, charts, and practical guidance to help researchers and practitioners choose appropriate FAHP approaches. The techniques are categorized based on four key aspects of developing a fuzzy AHP model: (i) representing the relative importance in pairwise comparisons, (ii) aggregating fuzzy sets for group decisions and weights/priorities, (iii) defuzzifying a fuzzy set into a crisp value for final comparison, and (iv) measuring the consistency of judgements.

The study by Fabiano Castro Torrini et al. (2015) [16] analyzes electricity demand growth in Brazil and emphasizes the need for long-term forecasting. It compares a fuzzy forecasting model with the Holt two-parameter method and official EPE projections, finding that the fuzzy model generally provides more accurate results, with significantly lower forecasting errors. While the fuzzy model slightly overestimates demand in most sectors, it performs best in residential, commercial, and industrial categories, though it is less effective for the "other sectors" group due to unaccounted factors. A top-down disaggregation approach is used to generate subsystem-level forecasts, proving useful despite limitations in capturing individual series behavior. Overall, the results offer valuable insights into long-term energy demand, with future studies recommended to adopt bottom-up methods and include additional explanatory variables for improved accuracy.

The review of Adilet Yerkin et al. (2025) [17] highlighted the important role of fuzzy logic in contemporary computer vision applications. A key strength of fuzzy logic-based algorithms lies in their capacity to manage uncertainty effectively. By integrating fuzzy logic, low-level feature extraction, an essential basis for computer vision, is enhanced. In contrast to deep learning approaches, which often function as "black boxes", fuzzy systems offer clear, rule-based decision-making, thereby improving transparency and interpretability. Moreover, fuzzy techniques typically require fewer labeled training samples, making them particularly useful in environments characterized by limited or noisy data. As a result, fuzzy logic is well suited for computer vision tasks such as image segmentation, object detection, and scene interpretation, where ambiguity is common. Despite these advantages, fuzzy logic also has notable drawbacks. Designing appropriate membership functions and formulating effective fuzzy rules can be challenging and generally depends on the availability of domain experts.

The study of R. Parvathi et al. (2025) [18] introduces a new theoretical framework for surface pattern recognition that integrates fuzzy reasoning with graph-based representation to address both structural complexity and feature uncertainty. By modeling surface textures as graphs enhanced with fuzzy membership functions and inference, the approach enables context-aware and uncertainty-resilient recognition. The framework overcomes limitations of traditional, purely fuzzy, and graph-based methods, offers flexibility and interpretability, and provides a foundation for future intelligent and adaptive systems. Its applicability spans multiple domains, including industrial inspection, medical imaging, and biometrics, with strong potential for advancing next-generation AI models.

Fuzzy logic - based decision support systems (DSS) hold significant promise for advancing medical diagnostics. By explicitly handling the uncertainty inherent in clinical data, these systems can deliver diagnostic outcomes that are more accurate, reliable, and interpretable than those produced by traditional approaches. The study of Anurag Srivastava et al. (2025) [19] underscores the wide-ranging applications of fuzzy logic across areas such as medical image analysis, data mining, expert systems, and predictive modeling. The have the opinion that future investigations should explore the role of fuzzy logic in emerging healthcare fields, including bioinformatics and personalized medicine, while also tackling current limitations related to scalability and real-time deployment. Owing to their capacity to combine fuzzy reasoning with advanced technologies such as artificial intelligence and deep learning, fuzzy systems are poised to play a central role in the evolution of intelligent healthcare, offering new opportunities to enhance diagnostic precision and operational efficiency.

The study of Sumit Kumar Singh et al. (2023) [20] addresses the challenge of melanoma detection by combining fuzzy logic–based image segmentation with an enhanced deep learning approach. Advanced pre-processing techniques are used to improve dermoscopic image quality by removing artifacts and enhancing contrast. A modified YOLO deep convolutional neural network, strengthened with additional layers, residual connections, and multi-scale feature fusion, is applied for lesion detection. Experimental results show that the proposed method achieves higher accuracy and faster performance than existing classifiers when tested on standard dermoscopic image datasets.

The study of Bilal Cemek et al. (2025) [21] compares fuzzy logic based and machine learning models for predicting soil temperature at different depths (5, 10, 20, 50, and 100 cm.) using long-term data (collected between 2016 and 2024) from Tokat, Türkiye. Performance evaluation shows that the adaptive neuro-fuzzy inference system (ANFIS) outperforms other methods, followed by random forest and extreme gradient boosting. The results demonstrate that integrating fuzzy logic with machine learning enhances soil temperature prediction accuracy, contributing to precision agriculture and improved resource management.

Dr. Swapnil B. Mohod et al. (2025) [22] highlight the need for intelligent and adaptive clinical decision support systems capable of handling uncertainty and imprecision in medical data. It examines the integration of fuzzy logic into expert systems, showing how fuzzy reasoning improves diagnostic accuracy, interpretability, and clinician trust compared to traditional rule-based approaches. The study reviews system design, applications, and hybrid models combining fuzzy logic with AI, machine learning, and IoT, while also addressing implementation challenges. Case studies demonstrate strong alignment with expert decisions, particularly in ambiguous situations, underscoring the role of fuzzy expert systems in advancing precision, explainable, and patient-centered healthcare.

The study of Ionut Nica et al. (2024) [23] presents a bibliometric analysis of research on fuzzy logic and artificial intelligence in financial analysis from 1990 to 2023 using Web of Science data. The results show rapid growth in publications, strong international collaboration, and high citation impact, with leading contributions from key fuzzy systems journals. The findings highlight the increasing importance of fuzzy information granulation as both a mathematical foundation and a practical tool, demonstrating the expanding role of fuzzy logic and AI in transforming financial and banking analysis worldwide.

The study of Gülay Demir (2025) [24] provides a bibliometric analysis of MCDM (Multi-Criteria Decision-Making) and fuzzy MCDM research from 2014 to 2024, revealing rapid growth in publications but a decline in citations per article. It identifies leading journals, influential authors, and productive institutions and countries, with China dominating research output with 14,545 publications and 122,430 citations, followed by India, Pakistan, and Turkey, whose collaborative efforts contribute to increased global research interaction. Key trends include the growing role of fuzzy logic, increasing integration with machine learning, and expanding applications in sustainability-related domains, highlighting strong prospects for future AI-driven decision-making models.

The study of Chukwudi Obinna Nwokoro et al. (2025) [25] reviews eleven years of research on picture fuzzy sets, highlighting their evolution from traditional fuzzy sets to multi-valued uncertainty models that better handle ambiguity through a neutrality component. Based on a comprehensive analysis of literature from major databases between 2013 and 2024, the study identifies strong research activity in healthcare, transportation, and other fields, with major advances in aggregation operators, similarity measures, and MCDM applications. It identifies MCDM as a major application area while noting that many studies remain theoretical. The review also points out challenges such as computational complexity and scalability, suggesting the need to explore generalized models and expand practical applications, particularly in developing improved distance measures.

The study of Citlaly Pérez-Briceño et al. (2025) [26] reviews the role of artificial intelligence in enhancing photovoltaic (PV) systems through improved efficiency, predictive maintenance, and fault detection. Using a systematic literature review and bibliometric analysis, it identifies key AI techniques and their applications, highlighting maximum power point tracking (MPPT) as the most researched area, followed by forecasting, parameter estimation, and fault diagnosis. The analysis shows rapid growth in AI–PV research from 2018 to 2024, led by China, the United States, and Europe. The study also presents a type-2 fuzzy logic–based tool in MATLAB to assist in selecting suitable AI methods, and outlines practical implications and future research directions for advancing AI-driven solar PV technologies.

Stella Hrehová et al. (2022) [27] have developed a fuzzy logic–based predictive model using soft computing techniques to analyze heating demand in a railway station, where gas consumption is primarily driven by outdoor temperature. Average outdoor temperature serves as the key input parameter, enabling clear graphical interpretation of results. However, the use of average values introduces some inaccuracy, particularly due to unexpected temperature fluctuations. The study suggests improving the model by accounting for the frequency of such fluctuations in the fuzzy rule base, with future work aimed at validating this enhancement.

Mallareddy Adudhodla et al. (2025) [28] have introduced a real-time fuzzy logic–based model for adaptive driver drowsiness detection using a Mamdani-type inference system with fourteen predictors related to decision-making, criticality, eye behavior, and driver experience. By processing normalized real-time data, the modular framework captures subtle changes in driver state and environment. The results show that the model achieves accuracy comparable to machine learning methods while reducing computational complexity and improving interpretability. Evaluated using RMSE and MAE, the system proves robust for real-time use and offers an effective, transparent solution for enhancing driver assistance and road safety.

e-Governance in India plays a vital role in modernizing public administration and improving citizen–government interaction through the use of ICT. Irshad Khan et al. (2025) [29] have reviewed its evolution from early pilot projects to major national initiatives such as NeGP and Digital India, highlighting improvements in transparency, accountability, service delivery, and citizen empowerment. They also discuss practical applications through initiatives like the e-District project. Despite significant progress, challenges such as the digital divide, cybersecurity concerns, infrastructure gaps, and resistance to change remain, especially in rural areas. They conclude by emphasizing the future potential of technologies like AI, blockchain, and IoT, along with policy measures needed for sustainable e-governance growth.

3. Materials and Methods

3.1. Fuzzy Relation

Consider the Cartesian Product

$$A \times B = \{(x, y): x \in X, y \in Y\},$$

where A and B are subsets of the universal sets V_1 and V_2 respectively.

A fuzzy relation on A× B denoted by R or R (x, y) is defined as the set -

$$R = \{((x, y), \mu_R(x, y)): (x, y) \in A \times B, \mu_R(x, y) \in [0,1]\},$$

where $\mu_R(x, y)$is a function in two variables called membership function.

3.2. Fuzzy Logic

Fuzzy logic is a type of multi-valued logic that focuses on reasoning with degrees of approximation instead of relying on rigid, precise, and binary judgments.

Example 1:

"Today is sunny" might be

100% true if there are no clouds,

80% true if there are a few clouds,

50% true if it is hazy, and

0% true if it rains all day.

Example 2:

"Today is hot" might be

100% true if the room temperature is greater than 40^o C,

80% true if the room temperature is above 33^oC and below 40^o C,

50% true if the room temperature is above 25^oC and below 30^o C, and

0% true if the room temperature is below 25^oC.

Consider

p: Today is sunny

q: Today is hot

T_4 = {0, 1/3, 2/3, 1}

Here 100% true is denoted by 1

80% true is denoted by 2/3

50% true is denoted by 1/3

0% true is denoted by 0

i.e. 100%, 80%, 50%, 0% truth values are denoted by 1, 2/3, 1/3, 0 respectively.

We know that

$$\vec{p} = 1 - p, \vec{q} = 1 - q$$
$$p \wedge q = min(p, q)$$
$$p \vee q = max(p, q)$$
$$p \rightarrow q = min(1, 1 + q - p)$$
$$p \leftrightarrow q = 1 - |p - q|$$

Fuzzy logic is a reasoning framework designed to manage imprecision rather than exactness. Unlike traditional binary logic that is limited to true/false or 1/0 outcomes, fuzzy logic allows for varying degrees of truth, with values spanning continuously between 0 and 1 to express partial truth.

This method is particularly beneficial in systems where binary logic cannot adequately represent complex and ambiguous scenarios. For instance, fuzzy logic is frequently utilized in control systems, such as those in household appliances, automotive systems, and industrial processes, to manage uncertainty and make decisions based on imprecise or subjective data [30].

The flexibility of fuzzy logic and its ability to handle uncertainty make it an important and effective approach for a wide range of applications in engineering, artificial intelligence, and decision-support systems.

Bojadziev and Bojadziev [31] state that the core concept in fuzzy sets is membership. This concept defines the relationship that connects each element to the set.

Let $X \subset R$ is a universal set and $A \subset X$. The membership function $\mu_A: X \to [0,1]$ denotes the membership grade of an element x to the set A, i.e.

$$\mu_A(x) = \begin{cases} 0, & \text{if } x \notin A \\ r, & \text{if } x \text{ belongs to } A \text{ with degree } r, 0 < r < 1 \\ 1, & \text{if } x \in A \end{cases}$$

Here [0,1] is the range of the membership function. A fuzzy set has the following representation

$$\tilde{A} = \{(x, \mu_A(x)) : x \in X\}.$$

If X is a discrete universal set, i.e., X= {x_1, x_2, x_3, …, x_n}, we have-

$$\tilde{A} = \{(x_1, \mu_A(x_1)), (x_2, \mu_A(x_2)), (x_3, \mu_A(x_3)), \dots, (x_n, \mu_A(x_n))\} \tag{1}$$

The selection of a membership function is influenced by various factors, including the context and the specific application. Common types of membership functions include triangular, trapezoidal, normal (Gaussian), and other similar functional forms. However, simpler functions, such as triangular ones, are often preferred as membership functions (refer to *Figure 3*).

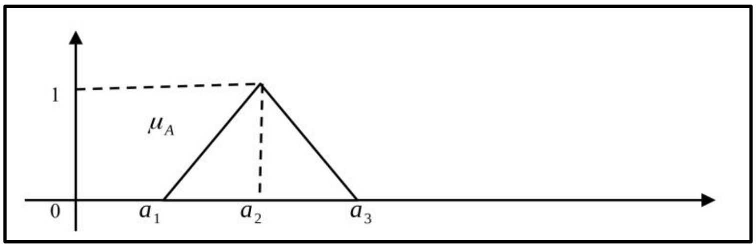

Figure 3: Membership Function μ_A

Operations defined on fuzzy sets typically include union, intersection, and idempotent operations. Given two fuzzy sets, A and B, the membership function for the union A∪B is expressed as:

$$\mu_{A\cup B}(x) = max\{\mu_A(x), \mu_B(x)\}.$$

Similarly, the membership function for the intersection A∩B is defined as:

$$\mu_{A\cap B}(x) = min\{\mu_A(x), \mu_B(x)\},$$

and A∪B=A, A∩A=A.

A fuzzy number serves as an example of a fuzzy set. A triangular fuzzy number is characterized by three parameters $(a_1, a_2, a_3), where\ a_1 < a_2 < a_3, with\ x = a_2$ representing the peak of the triangle (refer *Figure 3*).

The similarity between agents will be assessed through an additional competency index, reflecting a higher level of adherence to internal controls. As a result, governance improves when the evaluated agents align more closely with the ideal. This index between the fuzzy sets

$$A_1^{\Psi}, A_2^{\Psi}, \dots, A_n^{\Psi}$$

is given below:

$$\mu_{I_j^{\Psi}}^{X_i}(A_j^{\Psi}) = \frac{1}{n}\sum_{i=1}^{n} \mu_{I_j^{\Psi}}^{X_i}(A_j^{\Psi}), \tag{2}$$

where

$$\mu_{I_j^{\Psi}}^{X_i}(A_j^{\Psi}) = \frac{long\left(\left[b_{x_i}^1, b_{x_i}^2\right] \cap \left[a_{x_i}^1, a_{x_i}^2\right]\right)}{long\left(\left[b_{x_i}^1, b_{x_i}^2\right] \cup \left[a_{x_i}^1, a_{x_i}^2\right]\right)}$$

3.3 Linguistic Variables

Linguistic variables are variables whose values are described using words or phrases from natural language instead of precise numerical quantities. First introduced by Lotfi Zadeh in the 1970s, they form a core concept of fuzzy logic by enabling the modeling of complex and imprecise aspects of human reasoning.

Unlike traditional mathematical systems that use precise numerical values, linguistic variables describe qualitative attributes with terms like "high," "medium," "low," "fast," "slow," or "hot." These expressions are easier for humans to understand and relate to when reasoning about vague or uncertain concepts [31].

By using linguistic variables, systems can process and handle imprecise information in a manner that closely resembles human reasoning, enhancing their usefulness across many real-world applications.

A linguistic variable consists of words organized in an artificial language [3]. It is defined as a tuple (T, Ω, G, M), where T is the linguistic variable, Ω is the universe set, G represents the values of T, and M is a mapping of T to fuzzy subsets of X. In this context, T represents the name of the linguistic variable, while the characteristics of the enterprise are defined by the set G = {Very Good, Good, Regular, Bad, Very Bad} [4]. The numerical values assigned to each linguistic label fall within the range [0, 100]. Therefore, the universe set is Ω = [0, 100], and M comprises all the membership functions (refer to *Figure 2*). Each attribute will be evaluated using the labels listed in the first column of *Table 1*, and subsequently, a fuzzy triangular set will be constructed based on the collected data, as shown below:

Table 1: Fuzzy Triangular Numbers

Linguistic Variables	**Fuzzy Triangular Numbers**	**Fuzzy** $\varphi - Set\colon \left[a_{x_j}^1, a_{x_j}^2\right]$
Very Good	(66.4, 83, 100)	[66.4, 100]
Good	(49.8, 66.4, 83)	[49.8, 83]
Regular	(33.2, 49.8, 66.4)	[33.2, 66.4]
Bad	(16.6, 33.2, 49.8)	[16.6, 49.8]
Very Bad	0, 16.6, 33.2	[0, 33.2]

The chart on each membership function of the fuzzy triangular set is given by *Figure 4*.

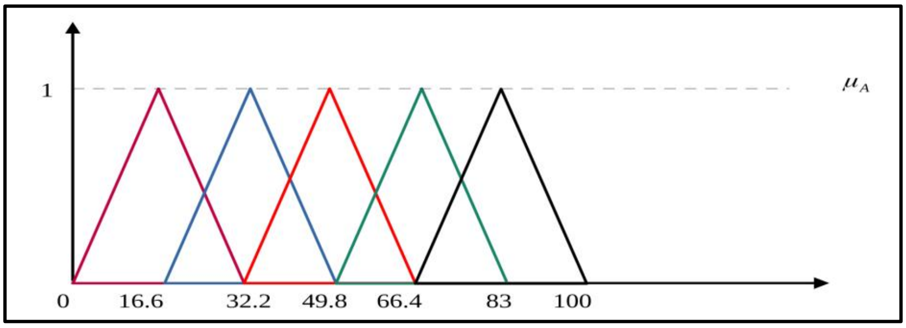

Figure 4: Graph of Fuzzy Triangular Numbers

4. Results

4.1 A Fuzzy e-Governance Model

The main objective of an e-Governance project is to offer the selected services at a more effective, efficient and smart way. Like any other governance processes, an e-Governance plan or programme is also liable to evaluation or audit. It helps the governments to take the necessary corrective measures to make the plan or progamme more effective to make the citizens benefited.

Here we are trying to check the applicability of the Fuzzy Governance Model, proposed by Enriqueta Mancilla-Rendon, et al [4], in case of e-Governance scenario with minimal necessary changes in the model.

It will be considered as a group of R categories assessed to determine factors such as project size, monetary investment level, transaction volume, workforce size, project leadership, and macro-economic context, among others. These categories will be presented in the following set:

$$X = \{x_1, x_2, x_3, \ldots\ldots\ldots\ldots, x_R\} \quad (3)$$

In addition, the external auditor will evaluate n agents (services):

$$A = \{A_1, A_2, A_3, \ldots\ldots\ldots, A_n\}.$$

Each of these agents is required to adhere to various internal control policies and procedures. A fuzzy logic–based model can be regarded as an effective tool for assessing the degree of compliance in the implementation and monitoring of policies and internal control procedures, which is crucial for strengthening corporate governance. The ideal agent (I) represents the entity that most fully satisfies each category and is defined according to the auditor's professional expertise and judgment. Thus, the fuzzy set is:

$$I = \{(x_1, [a^1_{x_1}, a^2_{x_1}]), (x_2, [a^1_{x_2}, a^2_{x_2}]), (x_3, [a^1_{x_3}, a^2_{x_3}]), \ldots, (x_R, [a^1_{x_R}, a^2_{x_R}])\}.$$

Set I is constructed using the data from Table 1. To assess the similarity between the agents under evaluation and the ideal agent, the categories of each will be compared to the ideal using the addition competency index.

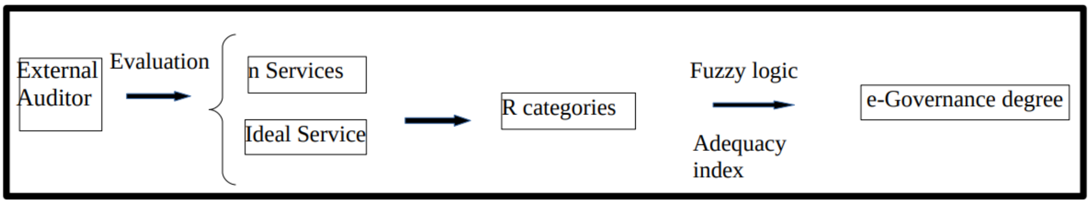

Figure 5: e-Governance Structure

4.2 Applications

In case of most of the e-Governance applications the success or failure of the applications could be measured on the basis of *Actual Usage of e-Governance Applications. Again, Public Trust*, *Service Quality* and *Information Quality* determine the Actual Usage of the Applications. So, in this example, the Fuzzy Model for e-Governance seeks to meet three categories:

X= {*Public Trust*, *Service Quality* and *Information Quality}*

Following the notation of Equation (3) we have a set of R=3 categories that will be evaluated in its processes X= $\{x_1, x_2, x_3\}$.

As an e-Governance project is launched to provide some selected G2G, G2E, G2C and/ or G2B services. Successful implementation of those services means the success of the project. But normally, it is noticed that out of those selected services few services get implemented successfully, some performs in an average level, and some get failed.

Ω= {Service-1, Service-2, Service-3, ………………….., Service-k}.

According to the experience and analysis carried out by the competent government authorities about the *Public Trust*, *Service Quality* and *Information Quality* regarding the services offered by a particular e-Governance programme or project are evaluated according to *Table 1*. The evaluations are shown in *Table 2*.

Table 2: Service evaluation (agents)

Attribute	A_1	A_2	A_3	A_4	A_5	A_6
Public Trust	Regular	Regular	Very Bad	Bad	Good	Good
Service Quality	Regular	Very Good	Regular	Good	Regular	Good
Information Quality	Regular	Good	Very Bad	Bad	Very Good	Regular

Following our proposed model (depicted in *Figure 5*) and considering Table 1, fuzzy sets with interval-valued membership functions for each service are built (refer *Table 3*).

Table 3: Fuzzy sets for Services (agents)

Attribute	A_1^{Ψ}	A_2^{Ψ}	A_3^{Ψ}	A_4^{Ψ}	A_5^{Ψ}	A_6^{Ψ}
x_1: Public Trust	[33.2, 66.4]	[33.2, 66.4]	[0, 33.2]	[16.6, 49.8]	[49.8, 83]	[49.8, 83]
x_2: Service Quality	[33.2, 66.4]	[66.4, 100]	[33.2, 66.4]	[49.8, 83]	[33.2, 66.4]	[49.8, 83]
x_3: Information Quality	[33.2, 66.4]	[49.8, 83]	[0, 33.2]	[16.6, 49.8]	[66.4, 100]	[33.2, 66.4]

It is important to note that the ideal agent is developed based on the independent auditor's professional judgment, skepticism, and expertise. This agent adheres optimally to each relevant category, meaning it meets the attributes outlined in *Table 4*, covering Public Trust, Service Quality, and Information Quality. To qualify as an ideal service, the Public Trust, Service and Information qualities should not exceed 83%, while each one of these must be at least 49.8%.

Table 4: Fuzzy sets for Ideal Services (agents)

Attribute	Ideal I	I^{Ψ}
x_1	Good	[49.8, 83]
x_2	Good	[49.8, 83]
x_3	Good	[49.8, 83]

Then, we use the addition competency index, Equation (2), between fuzzy sets $A_1^{\Psi}, A_2^{\Psi}, A_3^{\Psi}, A_4^{\Psi}, A_5^{\Psi}, A_6^{\Psi}$, and the ideal set I. To calculate $\mu_{I_j^{\Psi}}^{X_i}(A_j^{\Psi})$, the data in Table 3 and Equation (2) are used. Here n=3. We get the results that are summarized in *Table 5*.

Table 5: Adequacy index

Agent (Service)	$\mu_{I_j^{\Psi}}^{X_i}(A_j^{\Psi})$
A_1	0.33
A_2	0.55
A_3	0.11
A_4	0.33
A_5	0.55
A_6	0.78

Agents (Services) A_2 and A_5 demonstrate a notably higher adequacy index, while A_6 has the highest adequacy index, indicating that they adhere most effectively to the internal control process for the success of an e-governance plan. It has been observed that the Adequacy index reaches its highest value when all three attributes are rated as *Good*, and it declines when the value of any one of these attributes is either increased or decreased. It may be interpreted that rating *Very Good* rating of one attribute may also contribute declination in adequacy in some cases.

5. Discussion

e-Governance refers to the use of Information and Communication Technology (ICT) to provide public services to citizens in a reliable, transparent, and efficient manner, while maintaining cost-effectiveness. It helps citizens save money, fuel, and time by reducing the need to visit government offices, and also enables the government to cut costs related to office maintenance [32]. So, it benefits both the parties involved in the process of governance.

As in most of the services offered by the government involve two or more offices, there remains a need of proper coordination in activities among them. That is why, there remains district committees to discuss the issues to resolve.

Again, many e-governance plans include services from different government departments. One department may have to play its roles in offering one service fully or only their parts. So, there remains a need for better coordination among the departments. That is why, some state level, district level and circle/ block level committees are formed for coordinating and monitoring the e-Governance project related activities. These committees also perform the audit of the performance of the project. Also, in some projects there remain some implementing agencies, which may be some government departments or government agencies/ organizations.

The ultimate concerns of the committees/ agencies are to maintain and/ or uplift the *public trust* for the e-governance services, *service quality* and *information quality* of the services.

6. Conclusion

Our present work is an attempt to check the possibilities of implementing the Fuzzy Governance Model proposed by Enriqueta Mancilla-Rendon et al. [4] in e-governance, with necessary changes. We took *public trust*, *service quality* and *information quality* as attributes for our studies on the inspiration of the works of M. Bhuvana et al. [5] and treated the services offered by some e-governance programme as agents in our approach. We have found that there should be some balance in the attribute values to make the e-governance programmes successfully implemented. The attribute values *Bad* and *Very Bad* give negative contribution to adequacy, while the values like *Regular* and *Very Good* have similar types of contributions. So, we have to be cautious while noticing and analysing these observations. Here, the managements of e-governance services should try to provide the services keeping the values of all the attributes around satisfactory level as per the suggestions of the experts (rating level *Good*).

Conflict of Interest: The authors declare that they have no conflict of interest.

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