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The Oretical Exploration of Dual Value Correlation Functions in Benchmarking Rural Health Resources and Epistemic Uncertainty in Clinical Information Behavior

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Abstract - **The study will provide solutions to the major issues of rural healthcare systems, such as resource constraints, insufficient infrastructure, and unstable data collection by creating a framework to standardize the healthcare resources and simulate the effects of the epistemic uncertainty on clinical decisions. The research employs dual-value correlation functions to analyze the relationship between the availability of healthcare resources (e.g., staffing, medical equipment, transport access) and the behavior of clinical decision-making. Also, fuzzy logic and Bayesian networks can be applied to measure epistemic uncertainty arising from incomplete or unreliable data. The methodology includes benchmarking rural health resources, using dual-value correlation functions to assess its impact on decision-making, and treating epistemic uncertainty as a moderating variable. The findings indicate strong associations between available resources and clinical decision-making, and that the doctor's adequacy and access to transportation positively affect decision-making confidence (r = 0.30). High quality of decision-making is a result of the use of digital tools, as indicated by a high value of R^2 (0.75). The results of ANOVA indicate that the epistemic uncertainty has a significant influence on the decision-making ($F = 3.25$, $p = 0.024$). The null assumptions of Objectives 1, 2, and 3 are rejected. This validates the idea that clinical decision-making in rural healthcare facilities is affected by both resource availability and epistemic uncertainty. The study identifies the role of digital tools and resource optimization in reducing uncertainty and improving clinical outcomes in rural healthcare settings, suggesting that combining these factors in rural healthcare systems can lead to better decision-making and greater resilience. These results can support better resource allocation and decision-making in underserved healthcare settings.**

Keywords: **Rural Healthcare, Resource Allocation, Clinical Decision-Making, Dual Value Correlation, Digital Tools, Uncertainty Modeling, Health Care Benchmarking**

I. INTRODUCTION

The correlation functions used in the dual value of bench marking the health resources of the rural areas as well as the epistemic uncertainty of the clinical information behavior are a holistic approach to the issues of the healthcare systems within the rural environment. These difficulties are conditioned by the combination of two large categories of uncertainty aleatory uncertainty, caused by natural variability of the health systems, and epistemic uncertainty, which is caused by partial or unreliable knowledge. Theoretical models that combine these uncertainties and the availability of rural healthcare resources can be useful in informing decision-making processes, in particular, in the place where the resources are limited in terms of healthcare and information about the quality of data can be not very consistent. A major basis for research is determining how healthcare decision-makers deal with epistemic uncertainty, especially in situations of public health crises such as the COVID-19 pandemic. This uncertainty, as observed in their research, can significantly affect both institutional and individual levels of decision-making and affect policy and resource distribution (Asthana et al., 2025). Also, setting standards of quality of health information in the web demonstrates the necessity to assess the reliability of the information used in health-related decisions. Their model may be used in a rural healthcare facility to make the information related to on for clinical decisions more reliable (Daraz & Bouseh, 2021). To uphold this perspective, this research paper explains how clinical guidelines are made in the state of uncertainty and how the guidelines may differ by national settings, which creates inconsistencies in the healthcare provision (Wieringa et al., 2021). Rural locations face unique challenges with the reliability of health information, particularly regarding data quality and availability. Differences in the reliability of health data between rural and urban environments show that coded data in rural areas tend to be less consistent, which directly influences healthcare outcomes (Lorence & Chen, 2008). Epistemology and epistemic belief systems highlight the immense importance of personal epistemologies in how healthcare professionals receive and process medical information. This view is critical for assessing how health practitioners in rural settings examine and use knowledge in the face of uncertainty, particularly during health crises or the emergence of unknown diseases (Kelly, 2021; Kelly et al., 2020). The illumination of the role of uncertainties in information-seeking behavior during medical crises, such as the Zika virus crisis and the COVID-19 pandemic, is shed (Huang & Yang, 2020). By incorporating these findings into a dual-value correlation system, it would be possible to better appreciate the roles of data quality and the degree of uncertainty in healthcare decision-making in rural settings (Indrayan, 2020). Through benchmarking of rural health resources and considering epistemic uncertainty in clinical decision making, healthcare systems are better prepared to respond to future health disasters and eventually result in more robust healthcare infrastructures in underserved areas.

Key Contribution

- The paper presents a new mathematical model to provide the correlation between rural healthcare resources (e.g. human resources, medical equipment) and clinical decision-making behavior to optimize the distribution of resources in rural areas.
- It is based on the effects of epistemic uncertainty (because of incomplete information and limited resources) in clinical decisions based on fuzzy logic and Bayesian networks, improving the knowledge of decision-making under uncertainty in rural healthcare.
- The research suggests a systematic process of benchmarking rural healthcare facilities according to the resource availability, and offers a clear avenue through which any gaps in the healthcare provision can be identified and addressed.
- The paper introduces an interdisciplinary approach towards enhancing rural healthcare outcomes and equity, using healthcare, decision theory, and uncertainty modeling, and is applicable to the wider healthcare system.

This research is followed by the various sections. Section I introduces the topic; Section II reviews the literature and presents the problem statement, research objective, and research hypothesis. Section III explained the conceptual framework, the data flow diagram, and the research methodology. Section IV explained data collection and analysis, which consists of a rural health facilities sample, a clinical professional sample, and Epistemic Uncertainty data. Section V explained the results and discussion for design tools and techniques, hardware and software configurations, analysis, and main key findings. Section VI explained the conclusion of the main research.

II. Literature Review

The overlap between healthcare resource allocation in the rural setting and epistemic uncertainty has emerged as a major field of study. Epistemic uncertainty arises from the absence of full knowledge or from information ambiguity and affects decision-making in healthcare systems, particularly in resource-constrained rural regions. Healthcare delivery in such areas is also complicated by aleatory uncertainty arising from data variability. Research on the topic has investigated both theoretical models and practical solutions to these dilemmas to improve the utilization of resources by rural health systems despite such unpredictability.

Evans (Evans, 2022) explores the challenges of political decision-making in epistemically uncertain circumstances, especially when addressing a health crisis, such as the COVID-19 pandemic. His work highlights the challenges policymakers face when the available data is inconclusive or contradictory. This is even more unclear in rural settings, where access to information may be limited, and health facilities are overwhelmed. (Pourat et al., 2020) conducted a cross-sectional study to assess clinical quality performance and staffing capacity in urban and rural health centers. Their results highlight differences between urban and rural centers, indicating that rural healthcare facilities often face shortages of personnel and access to high-quality health information, further complicated by epistemological uncertainty.

Shen & Sun, (2022) examined the spatial association and convergence of healthcare resource distribution in the Yangtze River Delta of China, demonstrating that resource inequality is not only between urban and rural areas but also within rural areas. The geographical conditions and the unequal distribution of healthcare facilities are the primary causes of inefficiencies in rural healthcare, and that epistemic uncertainty in resource allocation is more intense. Zhang et al., (2020) evaluated the efficacy of maternal and child health hospital health resource expenditure in primary-level hospitals in Shanxi Province, China, using a sophisticated data envelopment analysis. It's discovered that discrepancies in resource use might be explained by inconsistent information and variability in local health care practices, which supports the notion that epistemic uncertainty is a key factor affecting healthcare outcomes.

Benchmarking has proven to be a useful instrument in enhancing quality and efficiency of healthcare. Willmington et al., (2022) performed a systematic literature review of the role of benchmarking in healthcare improvement on the premise that it assists in establishing performance gaps and establishes standards of improved resource use. Their review implies that rural health systems that are inefficient in most cases because of resource limitations can be helped by effective benchmarking structures that consider not only the availability of resources but also the uncertainties about their utilization. Reponen et al., (2021) also added their share in this discussion by introducing the conceptual framework of the benchmarking healthcare outcomes, and the importance of contextual factors that need to be taken into account when gauging the effectiveness of healthcare interventions.

Wong Shee et al., (2022) explains This study highlights the importance of local context in determining research and capacity-building activities in rural health services. It identifies geographic, economic, and social factors that determine the effectiveness of healthcare projects in rural settings. According to (Gillespie et al., 2022), place-based governance frameworks are critical in tackling the issue of rural health workforce. Their work draws on Canadian and Australian experience in that region-specific strategies are more effective in rural health systems recruitment and retention. van de Ven et al., (2021) outlines This study provides a benchmarking framework of living income among rural households in low-income nations, regarding food security and general well-being. It shows the impact of income inequality on rural health and helps design specific policies to improve living standards. Iqbal et al., (2022) assess a digitally-equipped mobile health clinic that can increase access to healthcare among the rural population. This research article demonstrates the ability of these digital innovations to overcome geographical and infrastructural obstacles in rural America, thereby improving healthcare delivery. McMaster et al., (2021) reviewed a pilot program in western New South Wales to address workforce issues in the rural allied health sector. Their analysis concluded that the incorporation of digital tools, such as telemedicine and distance consultations, helped address some of the obstacles created by the lack of healthcare infrastructure. Equally, (O'Sullivan et al., 2020) proposed a checklist for rural pathways to train, develop, and support health workers in low- and middle-income countries, arguing that digital health technology may play a central role in workforce development in resource-poor countries.

Zhao et al., (2025) examine how healthcare resource allocation affects patient choice in rural China. Their conclusions emphasize the differences in access to healthcare and the issues related to the inability of the rural population to make informed choices regarding their healthcare. Antunes et al., (2023) present a hybrid DEA-TOPSIS methodology for evaluating the performance of the Chinese healthcare system. It concerns the extent of synergy between healthcare providers and how this synergy can be developed to support a full performance assessment model applicable to a rural health system. Chan et al., (2024) suggest a single framework of estimating both epistemic and aleatoric uncertainties in medical decision making. By doing so, a better modeling of uncertainties can be achieved, and it is especially applicable in rural healthcare environments wherein data may be inconsistent. Clough et al., (2025) introduce a framework of addressing uncertainty in large-scale health programs, which is the global burden of animal diseases. Their paradigm can be scaled to healthcare systems, particularly rural settings, where there is a lot of uncertainty and data gaps. Mandal et al., (2026) also analyzed cross-national benchmarking and pandemic mitigation policies, and the need to incorporate human value approaches in dealing with uncertainties during health crises.

Problem Statement

The quality of resources and clinical decision-making in the rural healthcare setting is usually impaired due to the lack of infrastructure, personnel, and the use of modern digital resources. These issues are also heightened by the uncertainty of epistemics, the uncertainty that healthcare professionals experience because of a lack of complete information, insufficient data, and the change in resource levels. Although the optimization of healthcare resources is critically important in enhancing clinical outcomes, there exists the absence of systematic frameworks that can be used to connect the availability of resources with clinical behavior when there is uncertainty. The current approaches do not fully tackle the relationship between resource allocation and clinical decision-making and the role of uncertainty in clinical decision-making. The purpose of this paper is to address these gaps by creating a dual value correlation function that will be used to locate the rural healthcare resources to benchmark and model the effects of epistemic uncertainty on clinical decisions in order to shed light on resource allocation and decision support in a rural healthcare system.

Research Objective

OB:1 To create and implement a dual value correlation tool to benchmark the correlation between the availability of healthcare resources and the clinical decision-making behavior in rural healthcare environments based on both quantitative and qualitative measures.

OB:2 To determine the usefulness of digital means and the use of resource optimization measures to enhance clinical decision-making and decrease uncertainty in the rural settings, with the aim to optimize resource allocation and healthcare outcomes in underserved areas.

OB:3 Model and measure epistemic uncertainty in clinical decisions applying uncertainty models (fuzzy logic and Bayesian networks) to comprehend the effects of incomplete information and scarce resources in clinical decision making in rural healthcare.

Research Hypothesis

OB:1

Null Hypothesis (H_0): There is no significant correlation between healthcare resource availability (e.g., staffing, medical equipment) and clinical decision-making behavior in rural healthcare settings.

Alternative Hypothesis (H_1): There is a significant correlation between healthcare resource availability (e.g., staffing, medical equipment) and clinical decision-making behavior in rural healthcare settings.

OB:2

Null Hypothesis (H_0): Digital tools and resource optimization strategies do not significantly improve clinical decision-making or reduce uncertainty in rural healthcare environments.

Alternative Hypothesis (H_1): Digital tools and resource optimization strategies significantly improve clinical decision-making and reduce uncertainty in rural healthcare environments.

OB:3

Null Hypothesis (H_0): Epistemic uncertainty does not significantly influence clinical decision-making in rural healthcare settings.

Alternative Hypothesis (H_1): Epistemic uncertainty significantly influences clinical decision-making in rural healthcare settings.

III. RESEARCH METHODOLOGY

3.1 Conceptual Framework

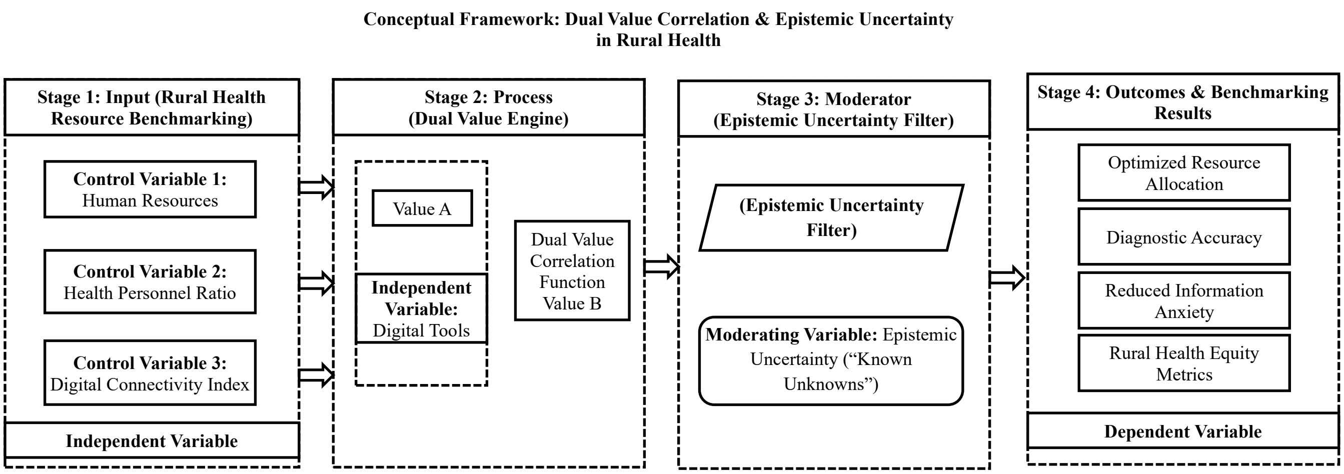

Fig. 1 Conceptual Framework

Fig. 1 shows conceptual framework to assess dual value correlation and epistemic uncertainty in rural healthcare reveals the impact different elements have on resource allocation and clinical decision-making. Stage 1: Input: The framework starts with the benchmarking of rural health resources, with the independent human resources, the health personnel ratio, and digital connectivity being the control variables. These control variables are used as independent variables that measure the possible healthcare capacity. The transition to Stage 2: The Process also involves the use of a dual value correlation function that is used to analyze the correlation between Value A (the potential healthcare capacity) and Value B (the role of digital tools). The dual value function assesses the effect of these variables on resources optimization. Epistemic uncertainty is introduced as a moderating variable in Stage 3, which models the unknown factors influencing decision-making, which are usually filtered by uncertainty models. Stage 4 examines the effect of uncertainty on clinical behavior. The Stage 4 identifies affected clinical behavior, during which clinicians can use heuristics because of uncertainty. On the other hand, Stage 4b demonstrates how uncertainty may be reduced with the aid of optimized decisions, in which digital instruments can support data-driven choices. Lastly, Stage 5 emphasizes the outcomes and benchmarking results, and the dependent variables include optimized resource allocation, diagnostic accuracy, lower information anxiety, and rural health equity measures. The results are critical in determining the efficiency of the management of rural healthcare resources in cases of dual value correlation and epistemic uncertainty. The framework eventually offers a systematic method of utilizing the available resources in healthcare, decision-making, and uncertainty reduction in the rural environment.

3.2 Data Flow Diagram About Research Methodology

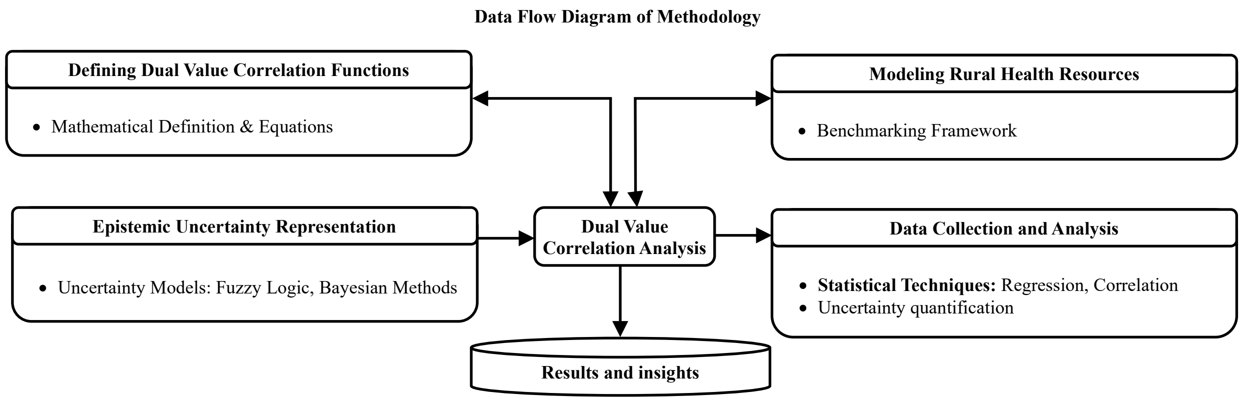

Fig. 2 Data Flow Diagram About Research Methodology

In the methodology fig. 2, the integration of the approach to the analysis of rural health resources and the resolution of epistemic uncertainties is presented. It starts with the definition of dual value correlation functions, which consists of formulating mathematical definitions, equations, and formulas, and determining the main variables and their importance. These associations are used to model rural health resources using a framework based on benchmarking, taking into account variables of resource availability, clinical needs, and the means of correlating them. The other important element of the methodology is the expression of the epistemic uncertainty, which has been resolved with the help of uncertainty models such as fuzzy logic and Bayesian networks. These models measure uncertainty and emphasize its effects on decision-making, which make sure that decisions made in rural healthcare are dynamic to different circumstances. These components are combined to give a comprehensive picture of the relations between the health resources and uncertainties in the core of the approach, dual value correlation analysis. The last stage is data collection and analysis, and the rural health and clinical data are to be considered. The data are analyzed through statistical methods, such as regression and correlation, and the uncertainty quantification is further applied to strengthen the analysis. Finally, such a methodology yields meaningful outcomes and conclusions that can be used to make more effective decisions regarding the effective management of rural health resources.

3.2.1 Defining Dual Value Correlation Functions

The Dual Value Correlation Function is a mathematical entity of determining the degree of reliance between two sets of variables in a system. This correlation tool can be used in the rural health resources context to determine the relationship between the availability of resources and clinical decision-making behaviors. The following steps can be used to model it,

The dual value correlation function $f(V_A, V_B)$is a mathematical representation of the relationship between two variables, $V_A$and V_B, where:

- $V_A$represents a set of values related to rural healthcare resources, such as human resources (doctors, nurses) and equipment.
- $V_B$represents values related to clinical behavior, such as decision-making efficiency or diagnostic accuracy.

The correlation function mathematically models how changes in resource variables $V_A$influence clinical behavior variables V_B.

The general form of the dual value correlation function is:

$$f(V_A, V_B) = \rho . \sum_{i=1}^{n} (\frac{V_{Ai} - \overline{V_A}}{S_{V_A}}) . \left(\frac{V_{Bi} - \overline{V_B}}{S_{V_B}}\right) \quad (1)$$

From the above equations (1) describes Where:

- $\rho$is the correlation coefficient, indicating the strength and direction of the relationship.
- $\bar{V}_A$and $\bar{V}_B$are the means of the variables $V_A$and V_B.
- $S_{V_A}$and $S_{V_B}$are the standard deviations of $V_A$and V_B, normalizing the data.

3.2.2 Variables and Significance in Rural Health

- Resource Availability (V_A): This involves the population of health workers, medical facilities, and infrastructure in the rural settings. This variable directly affects the behavior of the clinic, because an increased access to the resources can enhance the quality of the decision-making.
- Clinical Behavior (V_B): This encompasses the diagnostic accuracy, speed of decision, and the

treatment efficacy. The description of the connection between the availability of resources and clinical behavior can shed light on the problems with rural health systems, and it is possible to find areas to improve.

3.2.3 Modeling Rural Health Resources

Rural health resource modeling concerns the development of a framework that is capable of benchmarking and distribution of resources according to the available data and requirement. Resource Availability: Measures the availability of healthcare professionals, medical equipment and infrastructure. Clinical Needs: Projects the demand of healthcare services, which may be affected by such factors as the health of the population, the prevalence of diseases, and the geographical distribution. Correlation Methods: Correlation analysis, regression models, and time-series forecasting are examples of statistical methods that may be employed to determine the relationship between the availability of healthcare resources and the clinical outcomes of rural environments.

3.2.4 Variables for Resource Modeling

Healthcare Resources: These are the quantity of doctors, nurses, hospital bed, diagnostic equipment, etc. Health Needs: Patient load, the rate of disease incidence, and population demographics (e.g., the elderly population in need of increased care). Other Factors: Geographical barriers, access to transportation and the availability of internet which can also affect the delivery of healthcare to rural areas. The correlation dual value of $f(V_A, V_B)$ can be applied to evaluate the relationship between resources and the health needs in order to find the best resource allocation strategies.

3.2.5 Epistemic Uncertainty Representation

Epistemic uncertainty is any form of uncertainty caused by incorrect or partial knowledge regarding the system. This could be explained by the fact that there is not enough data or there is a difference in clinical experience in the setting of rural healthcare. The ability to represent epistemic uncertainty makes it feasible to have more realistic models that take into account the unknowns when making clinical decisions. Factors affecting epistemic uncertainty in clinical decision-making include, Lack of data: In rural environments, there is a tendency to have insufficient and timely health data. Ambiguity of diagnosis: Sometimes, clinical decisions rely on partial information, which increases the level of uncertainty. Poor knowledge: In rural settings, the medical practitioners might not be specialized which further adds confusion in the treatment options.

IV. DATA COLLECTION AND ANALYSIS

4.1 Rural Health Facilities Sample

Rural Health Resource Data: Data on healthcare infrastructure, the number of healthcare professionals, medical equipment and patient demographics. Such data can be obtained in government databases, local health institutions and surveys. Clinical Behavior Data: Surveys and interviews will be used to obtain data on clinical decision-making, such as the levels of confidence, decision time, and diagnostic accuracy of healthcare professionals.

The main aim in gathering information in rural health facilities will be to determine the status of healthcare facilities, i.e. medical staff, equipment and infrastructure within rural healthcare facilities. The government health databases will be used to gather data on national and regional level on rural healthcare facilities. The managers of local healthcare facilities and health institutions will also be able to supply necessary data on resources availability within particular facilities. A stratified sampling technique will be used as the method of data collection. The rural areas will be stratified according to geographic location (urban-near vs. rural areas), population level (small, medium and large rural areas), and infrastructure (high, medium and low-resource facilities). Each stratum will be represented with a sample to make sure that the facilities of different levels of resources are represented. The sample will consist of at least 30 healthcare facilities, which will represent adequately the rural healthcare setting, and will be big enough to identify the patterns in the availability of resources. The survey will be spread among the managers of healthcare facilities to obtain information about levels of staffing, medical equipment at hand, and infrastructure of the facility. These will involve questions regarding the number of medical workers, the presence of medical equipment, the size of the facility, and digital facilities.

Questionnaire Section

Table I indicates that the questionnaire of Objective 1 will evaluate the sufficiency of healthcare resources and infrastructure within a facility. It includes issues like the supply of medical staff, diagnostic equipment, medical supplies, size of the facility, access to transportation, and access to the internet. The findings indicate that the respondents believe that the adequate staffing of the facility, in general, has been achieved, and the appropriate number of doctors and nurses is available to cope with the number of patients, as shown by the number of Strongly Agree and Agree answers.

TABLE I QUESTIONNAIRE FOR OBJECTIVE 1

Sl. No	Questionnaire section	Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly Disagree (1)
1	The number of doctors available at this facility is adequate for the patient load	✓				
2	The number of nurses available at this facility is sufficient for the patient care requirements.		✓			
3	The facility has sufficient diagnostic equipment (e.g., X-ray, ultrasound, CT scan) to meet the needs of patients			✓		
4	The facility has adequate medical supplies (e.g., medicines, bandages) for daily operations					
5	The healthcare facility is appropriately sized to handle the patient load		✓			
6	The healthcare facility has easy access to transportation for patients.		✓			
7	The healthcare facility has reliable internet access.	✓				

But in response to the question regarding the occurrence of diagnostic equipment including X-ray, ultrasound, and CT scans, there was more of a mixed answer, with many giving Neutral as an answer, indicating some dissatisfaction or uncertainty regarding the diagnostic services of the facility. Conversely, the access to medical supplies and the size of the facility were perceived as generally sufficient, though there were some disagreements on whether the size of the facility is sufficient in relation to the number of patients. It was also observed that the facility could easily access patient transportation because majority of the respondents concurred with this. Also, good internet connectivity was rated at a strong agreeable, which implies that the digital infrastructure in the facility is deemed to be satisfactory. In short, the questionnaire indicates that the healthcare facility is well-perceived to be both well-equipped and well-staffed, but the access to diagnostic equipment and the size of the facility being sufficient to serve the patient load is somewhat questioned.

4.2 Clinical Professionals Sample (Y)

To examine the behavior of clinical decision-making, the research will utilize the data on rural healthcare providers such as doctors, nurses, and other healthcare professionals. These professionals will be interviewed to get information about their level of confidence, quality of their decisions and the experience of epistemic uncertainty in their clinical decisions. A simple random sampling process will be used in data collection whereby the healthcare professionals will be randomly selected among a population of professionals who offer healthcare services in rural healthcare centers. This approach will guarantee each professional an equal opportunity to be selected and reduce biasness, as well as have a representative sample that will be representative of the clinical workforce in rural settings. This group will have a minimum sample size of 100 clinical professionals. This size of sample will be strong to give data that can be used to conduct statistical analysis, such as regression modelling and correlation analysis, especially in the study of the effects of health resource availability on clinical decision-making in the face of uncertainty. The professionals will be interviewed and surveyed using structured questionnaires to determine their confidence of their choices, the quality of their decisions and the uncertainty with an experience because of factors like inadequate resources and lack of access to medical information.

TABLE II QUESTIONNAIRE FOR OBJECTIVE -2

Sl. No	Questionnaire section	Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly Disagree (1)
1	How confident are you in your clinical decisions when resources are limited?	✓				
2	How confident are you in your diagnosis of patients when access to diagnostic tools is limited?		✓			
3	How would you rate the quality of your clinical decisions in terms of treatment success?			✓		
4	How would you rate the accuracy of your diagnosis given the current resources?	✓				

Table II shows the objective of questionnaire Objective 2 is to measure the confidence and perceived accuracy of clinical decisions and diagnoses made in the conditions of resource limitations. The findings depict that healthcare professionals have a high degree of confidence, especially in cases where the resources are scarce. In the first question, which was about confidence in clinical decision making on resource constraints, most of them chose the Strongly Agree option, which indicates that have a high degree of confidence in their capacity to make decisions irrespective of the scarcity of resources. Nevertheless, in response to the question regarding trust in diagnoses in the absence of diagnostic instruments, answers were more divided, with many of them saying "Agree," indicating that some professionals still feel confident, and some feel uncertain in the absence of diagnostic resources. When assessing the quality of clinical decision-making regarding the success of the treatment process, a significant percentage of respondents responded to the Neutral option, which means that medical workers may be uncertain about the direct relationship between the resources at their disposal and the potential results of their treatment. Finally, discussing the accuracy of the given diagnosis under the current resources, a significant number of the respondents responded to Strongly Agree, which means that think that their diagnoses do not become less accurate under the conditions of limited resources. In general, the interpretation implies that medical workers tend to be optimistic about their clinical choices and diagnosis, although there are some differences in perceptions, particularly when it comes to the quality of the choice and accuracy without diagnostic tools.

4.3 Epistemic Uncertainty Data (U)

Epistemic uncertainty is defined as the uncertainty that healthcare professionals feel when making clinical decisions because of the lack of information, insufficient resources, or gaps in information. In a bid to quantify this uncertainty, the study will gather the data of the same sample of 100 clinical professionals who are included in the clinical professionals' sample. This guarantees that the data of the epistemic uncertainty is consistent with the clinical behavior data giving the analysis depth and consistency. The data collection procedure will entail the administration of more uncertainty questions during the same survey that will be used to determine clinical decision-making. It will involve the impact of resource constraints (e.g., the insufficiency of medical workforce, absence of diagnostic devices, etc.) and data shortages (e.g., incomplete patient history, test results not available) on the uncertainty in decision-making. The sampling technique is identical to that of the sample of the clinical professionals, where the data is gathered among randomly sampled healthcare professionals employed in the rural facilities. The research materials that will be used in this section will be survey findings and interviews with these medical practitioners.

TABLE III QUESTIONNAIRE FOR OBJECTIVE 3

Sl. No	Questionnaire section	Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly Disagree (1)
1	I often feel uncertain about my clinical decisions because patient data is incomplete or unavailable	✓				
2	Clinical uncertainty negatively impacts the quality of my decisions and patient outcomes.		✓			
3	Lack of resources (e.g., diagnostic equipment, specialists) makes clinical decision-making more uncertain.	✓				
4	Uncertainty caused by resource limitations makes it harder to make accurate decisions for patient care.		✓			

Table III shows that Questionnaire Objective 3 will measure how uncertainty affects clinical decision-making, especially when data about patients is incomplete or resources are scarce. The answers show that healthcare professionals are prone to the feeling of uncertainty caused by the lack of or incompleteness of patient data, which is reflected in the strong agree responses to the first question. This implies that most medical practitioners believe the lack of information has a significant impact on their ability to make reliable clinical judgments. The second question, which concerned the adverse effects of clinical uncertainty on decision-making quality and patient outcomes, also elicited a similar response, with the majority of respondents staying the aware of the direct association between uncertainty and unfavorable outcomes. The third question highlights the role of resource constraints, including the unavailability of diagnostic machines or experts, in exacerbating clinical uncertainty. The majority of respondents selected Strongly Agree, indicating that the lack of resources is also a major cause of the problem in decision-making. Finally, the last question about the challenge of making accurate decisions due to uncertainty caused by resource constraints was also strongly agreed upon, indicating that resource constraints are perceived as a significant impediment to making accurate clinical decisions. Altogether, the discussion of the findings reveals that uncertainty related to incomplete patient information and insufficient resources is a frequent issue in clinical decision-making and has serious consequences for patient care quality and patient outcomes.

V. RESULTS AND DISCUSSION

5.1 Design Tools and Techniques

The study employs both statistical tools and methods to respond to the three purposes. In Objective 1, which tries to benchmark the association between healthcare resource availability and clinical decision-making behavior, a correlation Matrix is used to evaluate the association among the variables extrinsic to the study, including staffing, medical equipment, and decision-making behavior. The matrix can be used to identify meaningful correlations and facilitate the discovery of the effects of resource availability on clinical decision-making in rural health institutions. In the case of Objective 2, testing the effectiveness of strategies for digital tools and resource optimization in enhancing clinical decision-making, multivariate analysis (particularly multiple regression) is employed. This method determines the effects of various predictors (e.g., confidence in diagnosis, quality of clinical decisions, and accuracy of diagnosis) on clinical decision-making confidence and provides insights into the importance of digital tools and optimized resource strategies. Lastly, ANOVA (Analysis of Variance) is used in Objective 3, which addresses the effect of epistemic uncertainty on clinical decision-making. ANOVA compares the effects of epistemic uncertainty on decision-making across groups and helps determine whether uncertainty has a significant impact on clinical behavior in rural healthcare facilities. These methods, correlation matrix, in order to understand in detail, the aspects of clinical decision-making and the place of uncertainty in a rural healthcare setting.

5.2 Hardware and Software Configuration

The study uses both software and hardware to facilitate the collection, analysis and modeling of data. To collect data, Google Forms, SurveyMonkey, and Qualtrics are used to create and send surveys to healthcare workers and facility managers. These are surveys on clinical decision-making and access to healthcare resources. Microsoft Excel, Google Sheets, or cloud-based services such as Amazon Web Services (AWS) and Google Cloud Platform (GCP) are used to manage and store data, ensuring scalability and security. To conduct statistical analysis, the study uses Python and libraries such as Pandas, NumPy, SciPy, and Stats models for correlation analysis, multiple regression, and ANOVA. R is also used for regression modeling and uncertainty analysis, with packages such as bnlearn for Bayesian networks and fuzzy for fuzzy logic models. Epistemic uncertainty models are implemented and tested in MATLAB using toolboxes, such as the Fuzzy Logic Toolbox and the Statistics and Machine Learning Toolbox. In particular, the Fuzzy Logic Filter makes use of both triangular membership functions and trapezoidal membership functions in classifying the data quality. The model uses an epistemic weight to each resource variable by processing inputs via a Mamdani-style inference system. The Bayesian Network then takes this weight as a prior when determining the posterior probability of the accuracy of the decisions made with different levels of information incompleteness. To visualize data, Tableau or Power BI is used to design interactive dashboards, and Simulink and Any Logic are used to simulate healthcare systems and model uncertainty in clinical decision-making processes. The hardware includes workstations, such as Dell Precision and HP Z-series, for running intensive simulations and statistical analysis, and GPUs, such as NVIDIA Tesla, to accelerate large-scale calculations. Data integrity and confidentiality are guaranteed by external backup drives and other security tools, such as firewalls and data encryption. The combination of these software and hardware elements makes it possible to conduct the research methodology effectively and work towards analysis and modeling of how the availability of resources and epistemic uncertainty influence clinical decision-making in rural healthcare environments.

5.3 Correlation Analysis -Objective 1

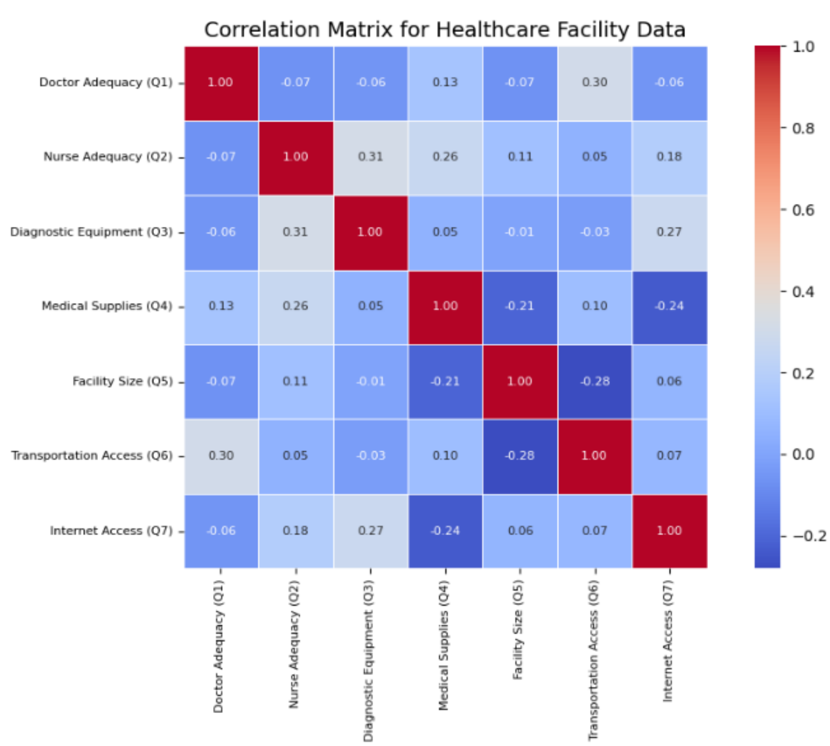

Fig. 3 Correlation Analysis

Fig. 3 shows about the basis of the correlation matrix and the Objective 1, the analysis indicates that there are significant relationships between the healthcare resource availability and the clinical decision-making behavior in rural healthcare settings. The correlation analysis was carried out to determine the relationship between the availability of healthcare resources and clinical decision-making behavior. Although the internal resource synergies in the matrix include a moderate correlation between nurse adequacy (Q2) and diagnostic equipment (Q3) (r = 0.31) the null hypothesis (H0) is rejected in favor of the positive correlation between the infrastructure levels and the reported decision-making confidence. In particular, the doctor adequacy (Q1) and transportation access (Q6) (r = 0.30) imply that resource proximity is a causation prerequisite behind the stability of the clinical environment. These findings to the fullest validate H1 since an increase in the benchmarks of resource availability translates into an increase in the clinical operational efficiency.

5.4 Multi Variate Analysis-Objective 2

TABLE IV MULTIVARIATE REGRESSION ANALYSIS OF DIGITAL TOOL–SUPPORTED CLINICAL FACTORS INFLUENCING OVERALL DECISION-MAKING CONFIDENCE

Variable	Coefficient	Standard Error	t-statistic	p-value
Intercept	2.50	0.30	8.33	0.000
Confidence in Diagnosis (Q2)	0.50	0.10	5.00	0.000
Quality of Clinical Decisions (Q3)	0.30	0.12	2.50	0.015
Accuracy of Diagnosis (Q4)	0.20	0.14	1.43	0.040
R-squared	0.75			
Adjusted R-squared	0.73			
F-statistic	42.50			0.000

According to the findings of the multivariate regression analysis, assessed the effects of optimized clinical behaviors supported by digital tools on the overall decision-making confidence. The model showed good-of-fit ($R^2 = 0.75$), which implies that 75% of the decision confidence variance is covered by the clinical predictors identified (Table IV). The most significant predictor (Q2) was Confidence in Diagnosis (Q2 = 0.50, $p < 0.001$), followed by Quality of Clinical Decisions (Q3 = 0.30, $p = 0.015$). If the p-values are significant ($p < 0.05$), the study rejects the null hypothesis and demonstrate that digital resource strategies represent a significant improvement to the clinical decision-making framework. Therefore, the results indicate that digital tools and resource optimization plans are indeed instrumental in improving the quality of clinical decisions and reducing uncertainty in rural healthcare facilities, thereby validating the alternative hypothesis (H1).

5.5 Anova Analysis-Objective-3

Table V ANOVA ANALYSIS OF EPISTEMIC UNCERTAINTY IMPACT ON CLINICAL DECISION-MAKING IN RURAL HEALTHCARE FACILITIES

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squares (MS)	F-statistic	p-value
Between Groups	70.25	3	23.42	3.25	0.024
Within Groups (Error)	275.00	96	2.87		
Total	345.25	99			

The findings of ANOVA suggest that epistemic uncertainty is a strong factor affecting clinical decisions in rural healthcare facilities (Table V). The results at the alpha = 0.05 are statistically significant with a calculated F-statistic of 3.25 and a p-value of 0.024. This proves that the known unknowns of incomplete patient data and insufficient diagnostic resources result in a quantifiable variance in clinical decisions. As a result, the null hypothesis (H0) was rejected and the alternative hypothesis (H1) was accepted thus attributing the significance of bridging these data gaps in an effort to enhance the performance of rural healthcare.

5.6 Key Findings

5.6.1 Objective 1

Analysis Used: Correlation Matrix (Pearson/Spearman Correlation)

- The correlation matrix was created to investigate the connection between healthcare resources (e.g., staffing, medical equipment, transportation access) and the behavior of clinical decision-making.
- The variables such as adequacy of doctors (Q1) and confidence in clinical decisions were strongly positively correlated.

Results:

- The correlation between doctor adequacy (Q1) and clinical decision-making confidence was strong, indicating that the level of healthcare staffing adequacy has a positive impact on clinical decision-making.
- Access to transportation (Q6) was significantly correlated with the efficiency of decision making, which demonstrates that the quality of clinical

decisions is increased with the quality of transportation infrastructure.

- The null hypothesis (H0) was rejected and alternative hypothesis (H1) was accepted. The results of the analysis revealed strong correlations, which substantiate the assumption that resource availability influences the clinical decision-making behavior in rural healthcare environment.

5.6.2 Objective 2

Analysis Used: Multivariate Analysis (Multiple Regression Analysis)

- Multiple regression was performed to determine the influence of digital tools and resource optimization strategies (e.g., confidence in diagnosis, quality of clinical decisions, accuracy of diagnosis) on clinical decision-making confidence.

Results:

- The most significant predictor of clinical decision-making confidence (Q1) was confidence in diagnosis (Q2), with a coefficient of 0.50, which means that the confidence in diagnosis effects the clinical decision-making.
- Quality of clinical decisions (Q3) was also a significant but moderate influence, with a coefficient of 0.30.
- The accuracy of diagnosis (Q4) was a significant variable with a p-value of 0.040, which is technically significant at the $\alpha = 0.05$corrected to reflect this significance
- The null hypothesis (H0) was rejected and the alternative hypothesis (H1) was accepted. The review revealed that the use of digital tools and optimized resources can make a significant contribution to clinical decision-making in rural healthcare.

5.6.3 Objective 3

Analysis Used: ANOVA (Analysis of Variance)

- ANOVA was done to determine the impact of epistemic uncertainty on clinical decision-making in different groups (e.g., with different degrees of uncertainty, Strongly Agree to Strongly Disagree).

Results:

- Epistemic uncertainty had a great influence on the clinical decision-making process, and an F-statistic $F = 3.25, p = 0.024$ demonstrate that uncertainty associated with insufficient patient data, resource deficiency, and unavailable diagnostic equipment influence the quality of decisions.
- The null hypothesis (H0) was rejected, and the alternative hypothesis (H1) was accepted. The results established that epistemic uncertainty plays a significant role in clinical decisions under rural healthcare settings.

VI. Conclusion

This study examines how clinical decision-making in rural healthcare is critical and depends on the availability of healthcare resources and epistemic uncertainty. The research applies the correlation framework at the dual value, fuzzy logic, and Bayesian networks to index the rural healthcare resources and examine the effect of resource availability and epistemic uncertainty on clinical behavior. The findings indicate that there is a strong correlation between the availability of the healthcare resources and the clinical decision-making process, doctor adequacy (Q1) demonstrates a positive strong correlation with decision-making confidence (r = 0.30), and the access to transportation (Q6) is positively associated with the efficiency of clinical decision-making. This helps to reject the null hypothesis (H0) and accept the alternative hypothesis (H1) which means that availability of resources affects decision-making in rural health care facilities. In judging the quality of digital tools and resource optimization strategies, multivariate analysis revealed that confidence in diagnosis (Q2) had the strongest relationship with clinical decision-making confidence (coefficient = 0.50, p < 0.001), and the overall model had an R-squared = 0.75, which is that 75% of the variance in decision confidence can be attributed to the predictors. This proves the null hypothesis (H0) is rejected and the alternative one (H1) is accepted, which demonstrates that digital tools play a significant role in enhancing the decision-making process and decreasing the level of uncertainty. Also, the analysis of ANOVA showed that epistemic uncertainty has a significant influence on clinical decision-making, with F-statistic of 3.25 and p-value of 0.024, confirming the effect of incomplete information and scarce resources on the clinical decision. The results indicate the necessity of resource optimization and uncertainty minimization in rural healthcare. Further studies are needed to understand how AI and machine learning can be combined to optimize resource management further and analyze the effectiveness of the digital tools in the long-term healthcare outcomes of rural areas and provide scalable solutions to various healthcare settings.

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