

## Research Article

# Construction of Rural Governance Digital Driven by Artificial Intelligence and Big Data

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Rural governance relies on distinct geographical, population, and fundamental service attributes for deploying digital construction and operation modes. The digital platform for rural governance includes surveying, identifying, and fulfilling the demands through application-specific user interactions. This article discloses a Modular Data Representation Method (MDRM) for improving the data semantics in digital platforms. The proposed method improves the presentation, analysis, and interaction in the governance process through requirements-based intelligent processing. The processing is performed based on the data organization as recommended by the regression learning paradigm. In this paradigm, the forward regression for data representation and service delegations are linearly analyzed. Based on the processing, the service requirement is met with big data availability. Therefore, the representation recommendations and data-driven analysis are provided through digital platform implications, improving the service availability. This is consistently provided based on the regressive outputs for data analysis. Therefore, the proposed method's performance is analyzed using the metrics analysis time, data processing rate, and unavailability.

## 1. Introduction

Rural governance is a process that provides various strategies and methods to improve the productivity, economic rate, and political and social development of the rural region. Rural governance introduces many methodologies to facilitate people and improves the lifestyle of village people [1]. Rural governance influences both local and administrative processes to provide better solutions for the people. Digital platform plays a vital role in constructing rural governance system. The digital platform increases the literacy level of rural people that improves their problem-facing capabilities of people [2]. The digital platform provides various helps for farmers, students, and other people in the rural region. Nowadays, various fields are digitalized by using certain technologies and methodologies that reduce unwanted problems in rural areas. Banks provide loans, policies, and schemes via digital platforms [3]. Farmers search for necessary information regarding seeds, plants, and weather conditions using a digital system. Digital-related services are

widely available in rural areas that provide necessary services to citizens using an Internet connection. Digital technologies ensure the safety of products that occurred via the traceable system and detection process in the rural governance system [4, 5].

Big data analysis is a process that uses certain analytic techniques to find out particular information from a large amount of data. The big data analysis process identifies the data that is necessary for performing a particular task in a system [6]. The big data analysis process is widely used in various fields that improve the performance and reliability of an application and systems. Rural governance system uses big data analysis process to enhance the accuracy rate in providing services for people [7]. Big data analysis provides comprehensive information services for various processes in the rural governance system. Services such as data collection, analysis, processing, and storage are provided using big data analysis. The big data analysis process is an important thing that is needed in the rural governance system [8]. A big data analysis platform allows rural governance to access a huge

amount of data that are needed to perform a particular operation. The big data analysis process reduces the latency rate and energy consumption rate in the identification process which improves the effectiveness of the rural governance system [9]. In rural governance systems, the big data analysis process reduces the complexity rate in accessing and processing huge amounts of data. Hidden patterns, features, and details are identified by a big data analysis process that provides actual information for performing a task [10].

Artificial intelligence (AI) is a process that uses human intelligence to perform tasks. AI is a subset of machine learning (ML) techniques that use ML to identify the patterns and features of data. AI is mostly used in computer-based applications to improve the efficiency and effectiveness of the system [11]. AI is widely used for data analysis processes that provide several ways to capture and process information. The data analysis process plays a vital role in various fields that enhance the performance and feasibility of the system. In rural governance, an AI-based data analysis process is used to provide necessary services for the citizens [12]. AI uses ML models to perform data analysis processes in the rural governance system. AI-based data analysis process performs a process such as modeling, preparing, producing, and identifying the necessary set of data [13]. Data analysis based on AI is used to find out the particular detail about the data that are presented in the storage. The convolutional neural network (CNN) model is mostly used in a rural governance system that improves the accuracy rate in the data analysis process. CNN improves the prediction rate that increases the development and construction process of the rural governance system. Bidirectional long short-term memory (BLSTM) is also used in the data analysis process that identifies the necessary information from the database and produces a feasible set of data [14, 15]. The main contribution of MDRM is shown below.

- (i) The solution under consideration enhances the governance process's display, analysis, and engagement by utilising requirements-based intelligent processing.
- (ii) As part of this paradigm, data representation and service delegation are both subject to a linear analysis of forward regression.
- (iii) Therefore, the representation recommendations and data-driven analysis are offered through digital platform implications, which improve service availability.
- (iv) Consequently, criteria like analysis time, data processing rate, and unavailability are used to enhance the effectiveness of the proposed technique

## 2. Related Works

Serrano and Zorrilla [16] introduced a reference framework for the fourth industrial revolution. A data governance system is implemented in the proposed framework to get an appropriate set of data for the analysis and accessing process. Data governance systems use big data analysis processes to find out the requirements for the identification process. The

big data analysis process reduces the latency rate in the searching process. The proposed reference framework improves the performance and reliability of industry 4.0.

Castro et al. [17] proposed a new ontology-based data governance model for the big data analysis process. Distributed component-based autonomous system is presented for data governance. An ontology represents all information that is related to data governance. The proposed method improves the accuracy rate in the decision-making process. Certain semantic techniques are used here to provide automatic ontology services. The proposed model also reduces the complexity rate in the management process which enhances the feasibility of the system.

Xu et al. [18] introduced a system dynamic analysis method for data governance. The proposed method measures the container port congestion and provides an actual set of data for the further analysis process. The main of the proposed method is to check the port congestion of containers and produce necessary information for the data governance process. Experimental results show that the proposed method increases the accuracy rate in the congestion evaluation process.

Zorrilla and Yebenes [19] proposed a reference framework for a data governance system in the fourth industrial revolution. The proposed reference framework identifies the key features and patterns of industry 4.0 that provide necessary information for the analysis process. Both cloud and edge computing systems are used in reference frameworks to perform governance processes. The proposed method improves the performance and effectiveness of the data governance system.

Xiao and Xie [20] introduced big data-based rational planning for smart cities. The proposed method improves the lifestyle of people in both rural and urban areas. The rural planning process provides appropriate ideas and techniques to improve the life quality of people in rural areas. Urban governance is implemented here to improve the construction capabilities of industries. When compared with other methods, the proposed method increases the effectiveness and efficiency rate of urban enterprises and industries.

Fürstenau et al. [21] proposed a platform management framework for digital health care systems. The proposed framework captures every detail about the patients and produces a final set of data for analysis and detection process. An evaluation process is performed here to find out the exact scaling and positioning of users in the health care system. The proposed platform management framework improves the efficiency and reliability of the system by reducing the complexity rate in the management process.

Jnr [22] introduced a new governance model for distributed ledger technology (DLT) in organizations. The governance model provides an appropriate set of details for the decision-making process. The proposed model improves the understanding of the organization that enhances the efficiency of the system. DLT identifies the key issues and problems in an organization that reduces unwanted problems. The governance model enhances the adoption of DLT which accelerates the digitalization process in an organization.

Liu et al. [23] proposed a decentralized service computing paradigm using a blockchain approach for a data governance system. The blockchain approach provides the necessary set of information for a data governance system that reduces the complexity rate. The big data analysis process is used here to manage a huge amount of data in the data governance system. The proposed governance system identifies the key instruction and issues using the computing paradigm.

Bosua et al. [24] introduced a data governance framework to measure the gender diversity rate in computer science. Public data is used here to get a relevant set of information for the identification and analysis process. The proposed data governance system analyses every detail of people and produces a final set of data for the measuring process. Public data is a collection of gender information that plays a vital role in the governance system. The proposed method increases the accuracy rate in the identification process which improves the efficiency of the system.

Petersen [25] proposed blockchain-based automatic governance for business networks. The blockchain approach identifies both traditional and conceptual functions in the governance process. The proposed method performs as interorganizational governance that improves the accuracy rate in the evaluation process. Blockchain finds out the important coordinates in the governance system that enhances the safety of the organization from the attackers. Experimental results show that the proposed method improves the performance and effectiveness of the system.

König [26] introduced a new data governance system for smart cities. Both legitimacy and ethical problems are identified by the data governance system. The proposed method provides appropriate solutions to solve problems. A data governance system improves the security level of both organizations and industries that enhance the reliability and feasibility of the system. The proposed method increases the accuracy rate in the decision-making process which provides better services for the users.

Malekpour et al. [27] proposed collaborative governance for urban areas. Key principles and features are first identified by using the collaborative method. Nature-based solutions are provided by a governance method that reduces the issues and error rate in the urbanization process. Preference and influence rate of people are identified and that is used for the decision-making process. The proposed method reduces the complexity level of the data governance process which improves the effectiveness and efficiency of the system.

Sagi et al. [28] proposed a data analytic process for data governance in smart urban areas. Machine learning (ML) techniques are used in the proposed method to improve the accuracy rate in the identification process. The artificial neural network (ANN) approach is used to find out the key issues and features of the governance system. The neighborhood shapes and levels are identified by the proposed method that improves the lifestyles of urban areas. The summary of related work is discussed in Table 1.

The big data analysis process reduces the latency rate in the searching process. The identification and the

development of data processing have less accuracy and produce less feasible data. Less development and construction process of the rural governance system are obtained from all classification methods. The proposed method enhances the performance and reliability of the system.

### 3. Modular Data Representation Method (MDRM)

Construction and operation modes of rural governance based on AI and big data analysis are becoming a continuous representation due to the growing population and fundamental service attributes on the digital platform. Amid the challenges in rural household perceptions such as living, production, and ecological spaces are the appropriate service requirements to satisfy people's wellbeing and solve social problems (loneliness, isolation, etc.) for rural place-based development. The community, regions, bottom-up, and place-based approaches are used to incorporate local people's needs, commitments, initiatives, and meanings are often regarded as precise meaning to improve rural development. Due to differences in living, development, and production between regions, the endowment factors between the regions also vary. The unequal distribution of needs, production, and means has decreased the growth of the agricultural economy and increased social problems. However, the average distribution of needs, commitments, and means of production does not in line with the actual development means and needs; therefore the solution is the rational distribution of needs and productions between the regions. The equality and adjustment of industrial structure through digital rural governance are mainly reflected in the investment in agricultural productions through the big data analysis. The proposed method is illustrated in Figure 1.

The big data analysis accurately predicts the demand of productions and needs based on the different regions. The big data in MDRM is linearity checked with data availability and data processing with few services and demands. The data processing and the data availability in the digital platform mainly depend on the users and the services. Based on the identification of the mobile population in previous statistical surveys, the digital platforms include surveying, identifying, and fulfilling the needs, productions, and demands through application-specific user interactions that require diverse services. Therefore, regardless of the needs and demands of the users/people, reliability in data representation and distribution is a prominent consideration. The proposed MDRM method is focusing on this consideration by artificial intelligence and big data information through available digital rural governance. In this proposal, service availability is administrable for people and their services with the available digital platforms.

The AI and big data users access their services through data representation and distribution using digital rural governance. MDRM method operates between the applications and users. In this method, availability and processing for the available services and linearity check are easily able to achieve data semantics for the different users and services. Further, this method aims to provide unavailability-less data

TABLE 1: Summary of related work.

Author	Finding	Limitation
Sagi et al. [28]	The paper's contribution to urban government is the recommendation of a smart and adaptive system targeted at designating the most suitable areas for urban administration given a certain period and circumstance.	The proposed method cannot be implemented to the ever-changing conditions of urban areas.
Malekpour et al. [27]	The framework further underlines that all of those factors must be taken into account with an eye toward their intended impact degree. We will utilise real-world examples from significant Australian urban development projects to demonstrate how our approach may be put into practise.	In addition, a bridge from experimental forums to continuous collaboration structures must be provided when necessary. Policy design and large institutional reform efforts are typically used to attain this goal.
König [26]	Ethics are translated into a set of governance procedures that are at the same time grounded in the conception of democratic oversight, which is at the heart of the framework	In addition, a bridge from experimental forums to continuous collaboration structures must be provided when necessary. Policy design and large institutional reform efforts are typically used to attain this goal.
Petersen [25]	Blockchain technology now gives the capacity to automate the formulation, verification, and implementation of private ordering among exchange parties. This should drive a re-evaluation of existing theories of interorganizational administration, according to the article's conclusion.	The framework built may be empirically validated, as well as prospects for further theoretical research, and investigates the practical implications of blockchain-based governance for practitioners.

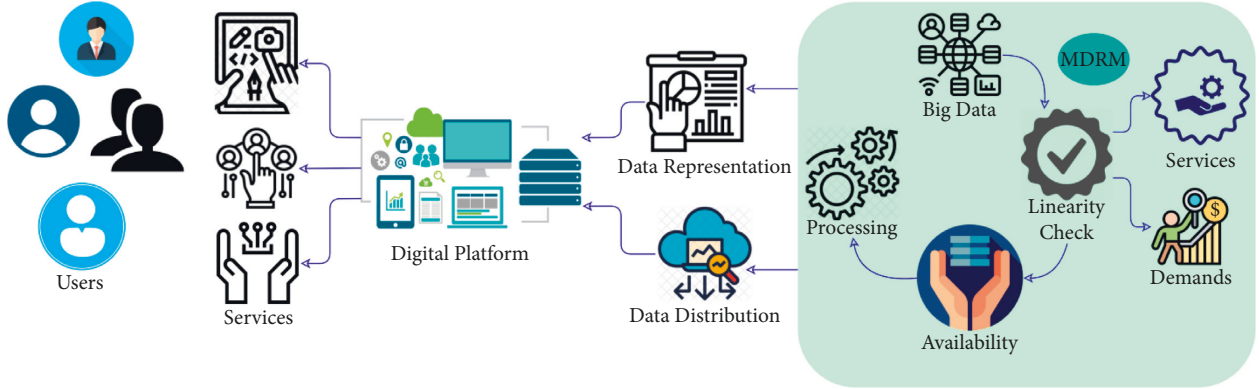


FIGURE 1: MDRM illustration.

processing and to maximize the available data distribution. The proposing method operates in two forms for data availability and processing concurrently. The data representation is different for service and delegations based on forwarding regression analysis, to check the big data availability of the users. The introducing function of the construction of digital rural governance is seen as in equations (1a) and (1b).

$$\left. \begin{array}{l} \max_{i \in t} \text{imize } u_s \forall D_r = D_d \\ \text{and} \\ \minimize at_i \forall D_r \end{array} \right\} \quad (1a)$$

where

$$\left. \begin{array}{l} at_i = t_{D_d} - t_{D_r} \\ \text{and} \\ \minimize_{i \in T} P_r \forall i \in D_r \end{array} \right\} \quad (1b)$$

In the above equations (1a) and (1b), the variables  $s, u, D_r, D_d$  denote the digital platform for rural governance

relies on  $i^{\text{th}}$  service, users, data representation, and distribution at different time intervals, respectively. The data are represented in the form of different services for rural governance  $D_r$  and the data availability  $D_d$ . The data processing  $D_r$  in the form of operation helps to achieve data semantics for the different users and services. In the next continuous representation, the variables  $at_i, at_{D_r}$ , and  $at_{D_d}$  are used to represent analysis time, data representation time, and distributing time, respectively. The big data analysis of minimizing the processing is represented using the variable  $P_r \forall i \in D_r$ . Let  $u = \{1, 2, \dots, u\}$  represents the set of users in the digital rural governance platform, then the number of services in the analysis time  $at$  is  $D_r \times t$ , whereas its data representation is  $u \times D_r$ . Based on the overall data representation,  $u \times D_r$  and  $t \times D_r$  are admissible services for data analysis. The data processing and availability are performed using presentation, analysis, and user interaction in the governance process through service requirements-based intelligent processing of the upcoming rural governance data processing. In this instance, the performance of data representation and pending services is important to identify big data information. The demanding service requirement is the

availability ( $A_n$ ) of the  $n$  rural governance users; the remaining time needed for data processing is the assisting factor for improving data representation. The data distribution of the service assigned for the available  $n$  is performed based on the data organization as recommended using logical regression learning. Later, depending upon the data distribution, the service requirement processing is the augmenting factor. For the data organization, big data analysis is the requirement-based intelligent processing instance for defining different data processing. The big data analysis-based services and the available data processing is important in the following session.

*Case 1. Continuous representation of services.*

*Analysis 1.* In this continuous representation, the data distribution of  $(D_r \times t)$  for all  $n$  based on  $A_n$  is considering big data analysis. The probability of surveying, identifying, and fulfilling the demands ( $\rho_d$ ) through application-specific user interactions in a continuous manner is given as

$$\left. \begin{aligned} \rho_d &= (1 - \rho_{cr})^{i-1}, n \in t \\ \text{where} \\ \rho_{cr} &= \left(1 - \frac{D_r \in n}{D_r \in t}\right) \end{aligned} \right\} \quad (2)$$

In equation (2), the variables  $\rho_d$  and  $\rho_{cr}$  represent user demands and the continuous data representation follows the probability of  $n$  such that there are no pending services in the digital rural governance; hence the data distribution is computed in the above equation (1a) and 1b. Therefore, the distribution of data for  $\rho_d$  follows:

$$\text{Distribution}(n) = \frac{1}{|D_d - D_r + 1|} (\rho_d)^i, \text{ if } \forall n \in t. \quad (3)$$

However, the data distribution for  $n$  as in equation (3) is valid in both the condition of  $(u \times D_r)$  and  $(t \times D_d)$  ensuring the data semantics in digital platforms. Figure 2 presents the data processing for continuous representation.

The data from different real-time sources (e.g. population, land, buildings, etc.) are surveyed yearly and updated. Based on the availability/update from the governance platform, the data is split into linear and nonlinear. The linear data is used for demand satisfaction and distribution. This is used for providing a complete data representation. Contrarily, the nonlinear data is further validated for its availability and assessment (Figure 2). The big data processing of rural governance information is based on user demands and needs to reduce the problem of the unequal distribution condition  $(u \times D_r) > (t \times D_d)$ , and the service requirement-based intelligent processing is descriptive using the representation. Therefore, the recommended conditions  $u > t$  and  $\rho_{cr}$  are less to satisfy equation (1a) and (1b). Hence, the contrary output of Case 1 is the prolonging continuous representation and therefore the analysis time, resulting in unavailability.

*Case 2. Linearity analysis for data representation*

*Analysis 2.* In the linearity check for data representation, the unbalancing condition of  $u > t$  is high, and therefore the distribution of services in the digital platform is time-invariant based on the data organization. Along with the idle time of  $n$ , the big data analysis and pending services are the considering factors. The probability of linearity analysis ( $\rho_{L_a}$ ) is given as

$$\rho_{L_a} = \frac{\rho_d \cdot \text{Distribution}(n) \cdot [(D_d - D_r) * \rho_{cr} - (D_d - D_r/n)u_s/t_{D_r}]}{f(d) \times n} \quad (4a)$$

where

$$f(d) \in \text{Distribution}(n) = \int_1^{D_r} at^{i-1} \cdot \frac{\rho_{cr}}{t_{D_r}} (1 - \rho_d)^{t-1} n(D_r). \quad (4b)$$

From equations (4a) and (4b), the variable  $f(d)$  denotes the data distribution function for services. For all the data distribution processing, the data availability in accessing services based on  $n$  is an unavailability issue. The distribution as in equations (4a) and (4b) requires high analysis time and thereby increases the data processing rate and service delay. Figure 3 illustrates the data representation based on linear validation.

The accumulated (surveyed) data (linear and nonlinear) is distributed using  $f(d)$ . This relies on  $f(d, S_d)$  differentiation for fetching previous data representation, and the nonlinear data is managed. After the representation, linear validation is performed for preventing unavailability (refer to Figure 3). As per the above big data analysis of Case 1 and Case 2, the differentiation of availabilities based on  $u > t$  in Case 1 and  $n$  overloading and analysis time are the considering factors. These factors are addressable using logical regression learning to mitigate the problems through regression analysis; the following section illustrates the data representation for the processing to mitigate the above determining issues.

*3.1. Availability and Processing Analysis Based on the Service Requirements Using Linearity Check.* The decisions for performing the availability process rely on logical regression learning. It aids availability for both continuous and discrete data instances. In Case 1 (Linear/continuous) and Case 2 (nonlinear/discrete), data processing is met with the big data availability using regression learning. The data representation process depends on different service requirements and attributes for analyzing the demands and service delegations probabilities at the time of data distribution. Hence, the cases for data distribution are different from the representation process, which follows the availability procedure through representation. The data representation is prescribed in Case1 and 2 by calculating the  $n$  available probability and representation of data for analyzing time.

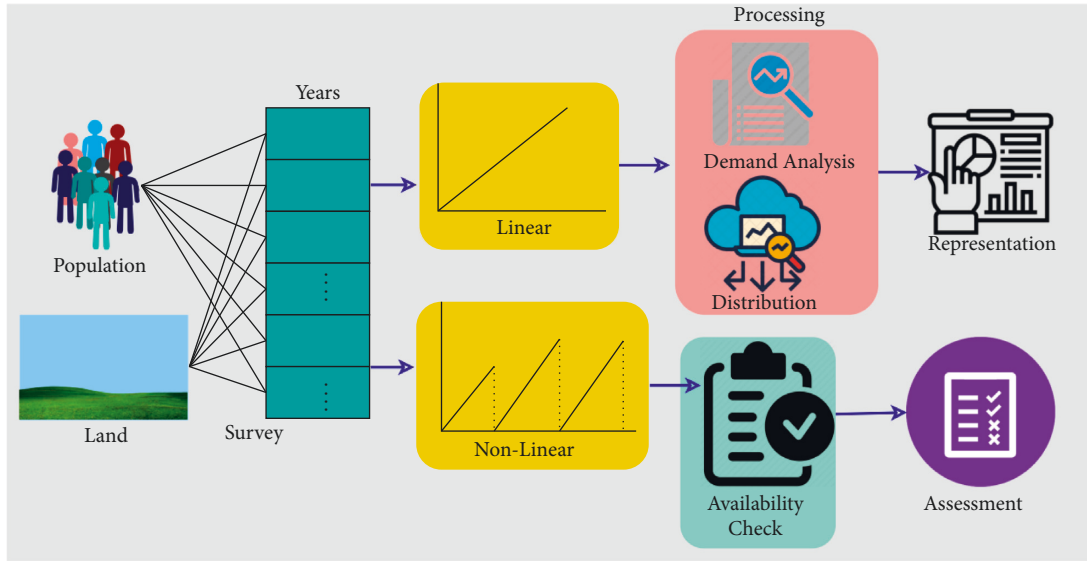


FIGURE 2: Data processing for continuous representation.

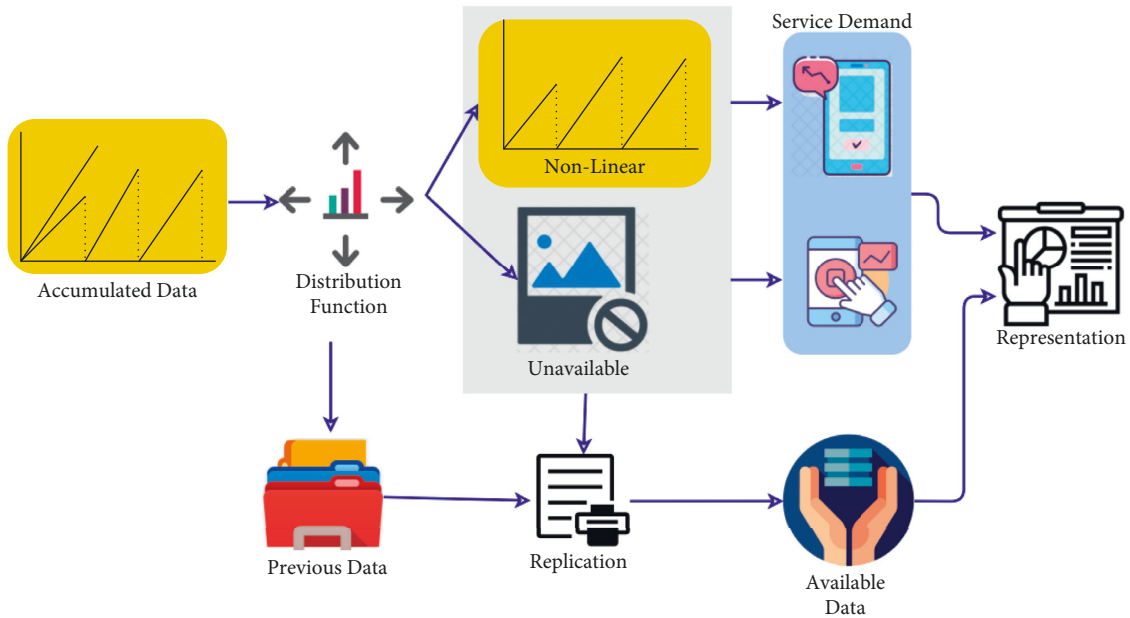


FIGURE 3: Data representation using linear validation.

The first data representation relies on maximum service delegations ( $S_d$ ) and  $f(d)$  as

$$\left. \begin{aligned}
 f(d, S_d) &= \left[ D_d - \left( \frac{at}{t_{D_r}} \right) + \frac{1}{n} \right] - Di \text{ stribution } (n) + 1 \\
 \text{such that,} \\
 n &= \sum_{i \in s} Di \text{ stribution } (n) - (\rho_{L_a})
 \end{aligned} \right\} \quad (5)$$

In the above equation (5), the forward regression for data representation and service delegations are linearly analyzed

depending on the distribution of the services in the digital platform for Case 1 as in  $\rho_d$  and Distribution ( $n$ ). Here, the chances of achieving continuous services are

$$\left. \begin{aligned}
 \rho_{L_a} \left( \frac{s}{d} \right) &= \frac{1}{\sqrt{2Nt^2}} \text{experssion} \left[ \frac{D_r - \rho_{cr}}{A} \right] \\
 \text{where} \\
 A &= \frac{D_r - \rho_{cr}}{n}
 \end{aligned} \right\} \quad (6)$$

In equation (6), the aim is to balance the users and services to reduce the analysis time, and hence, the actual data distribution is given as

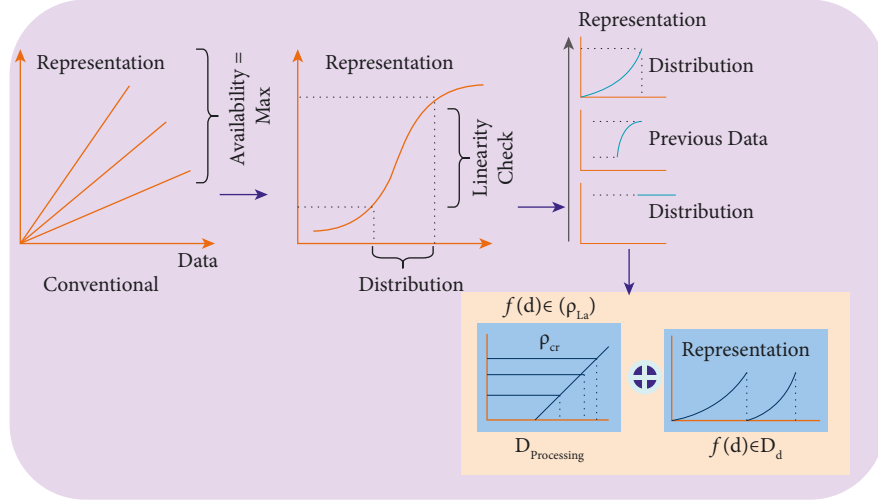


FIGURE 4: Regressive representation for distribution.

$$D_d = \max \left[ \frac{\rho_d \times D_r}{D_i \text{ distribution } (n) - \rho_{cr}} \right]. \quad (7)$$

Therefore, the availability is  $[1 - (\rho_d \times D_r / \text{Distribution } (n) - \rho_{cr})]$  and this availability based on the analysis time with the data processing instances of  $D_r$ . The excluding  $D_r$  is  $[D_r * f(a, S_d)]$  is the  $P_r$  instances and therefore the analysis time is demanding high. The bounds of analysis time based on demanding services (as per the distribution) in the rural governance are either of service (or) delegations, in both instances, if  $\rho_{cr} = 0$ , then  $A = D_r = D_d$  is the maximum availability condition and if  $\rho_{cr} = 1$ ,  $D_r = D_d - n$  or  $D_r = D_d$ . Hence, the occurrence of  $D_r = D_d$  is a regressive output. The analysis time for all the data representation (without processing) is given in equation (7). The regressive representation for distribution is depicted in Figure 4.

The data representation using logical regression is presented in Figure 4. The initial classification is based on linearity and distribution checks. In this process, the  $f(d) \in \rho(L_a)$  and  $f(d) \in D_d$  are classified for further analysis. Based on the analysis, data processing and augmentation are determined. In this scenario, the available users and services in the digital platform and the data representation and distribution are processed, hence the analysis time is consistent as in equation (1a) and 1b. The process of availability is  $(D_r - \rho_{cr} * n)$  and  $\sqrt{2\pi} (t)^2$ , this analysis determines the representation and analysis time along with the data processing rate for the processing  $D_r$ . The availability process of  $(D_r - \rho_{cr} * n)$  and  $\sqrt{2\pi} (t)^2$  from the available services is illustrated, respectively. The availability process of big data information is based on a linearity check for data representation and service delegations of  $(D_r, D_d)$  and  $(D_{rs-1}, D_{ds-1})$  based on available services from the data representation. The probability of  $\rho_{cr}$  and  $\rho_d$  and  $\rho_{L_a}$  is the considering factor for both types of availability processing as given in the above equation. The availability occurrences for  $(D_r, D_d)$  and  $(D_{rs-1}, D_{ds-1})$  is linearly analyzed based on  $S_d$  for  $f(d)$  is given as

$$\text{Availability } (n) = \begin{cases} \frac{n - (\rho_{cr} \times D_r)}{n + (\rho_d) D_r} \forall D_r = D_d. \\ \frac{n - (\rho_{cr} \times D_r)}{n + (\rho_d + \rho_{L_a} - \rho_{cr}) D_r} \forall D_r < D_d, \end{cases} \quad (8)$$

In this case of availability,  $n$  (or)  $(n - (D_r/A))$  is the data distribution irrespective of the users and services. In the next section of data representation, minimizing  $P_r = \{1, 2, \dots, D_r\}$  as from equation (8) is discussed to reduce unavailability and service delays.

**3.2. Processing.** The data representation recommendation and data-driven analysis follow either of the distribution as in equation (8). It is different for both the data representation and distribution as the first instance requires no more users and services, whereas the second instance requires distribution as  $(n - D_r)$  is the retaining data representation. As per the sequence in the previous section, the representation of data for  $P_r \in D_d = (n + 1) D_r / n$  is regressive and it does not require additional analysis time for processing. In the data processing ( $D_{\text{Processing}}$ ) of a service requirement in this data, distribution is the considering factor and it differs for each  $n$  depending on the availability of processing ( $n_p$ ). This analysis time is computed using equation (9) for both instances in equation (7)

$$D_{\text{Processing}} = \frac{n_p}{\text{Distribution } (n)} + \frac{f(a, S_d)(\rho_{cr} + \rho_{L_a} - \rho_d)}{\text{Distribution } (n)}, \forall D_d < D_r. \quad (9)$$

In equation (9),  $D_{\text{Processing}} \in [D_d, D_r]$  and the last of data processing (i.e.)  $(D_{\text{Processing}} * D_r)$  are the maximum analysis time and data processing rate (increase) for handling  $(n - D_r)$  representations. Therefore, the distribution of data for all  $s \in D_r$  increases both  $P_r$  and  $a_i \forall i \in D_r$ . This data

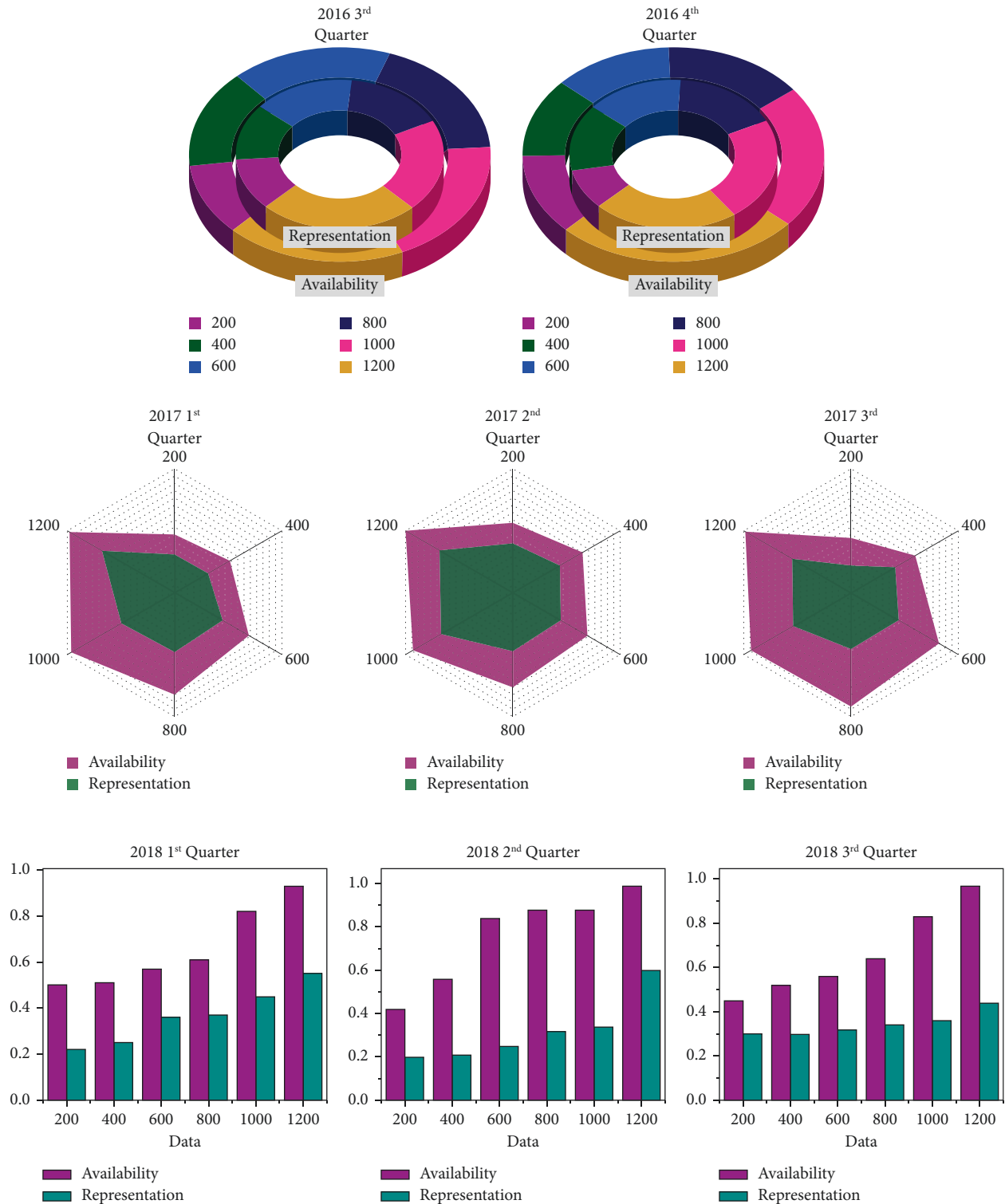


FIGURE 5: Availability and representation.

distribution process as mentioned above depends on available  $n$  users and services without requiring additional processing and relies on two instances of  $S$  distribution. The services in the digital platform performed under  $0 < \rho_A < 1$  in the previous service availability. The data distribution follows the condition  $0 < \rho_A < 1$  and  $\rho_A = 1$  of  $n$  services such

that the representation recommendation and data-driven analysis are performed. Here, the analysis time of service requirements is the sum of service delegations in two or more  $n$  that do not augment  $n \in \rho_r$ . Therefore, the unavailability is identified between processes of  $0 < \rho_A < 1$  and  $P_r = 1$  processing without increasing the availability and



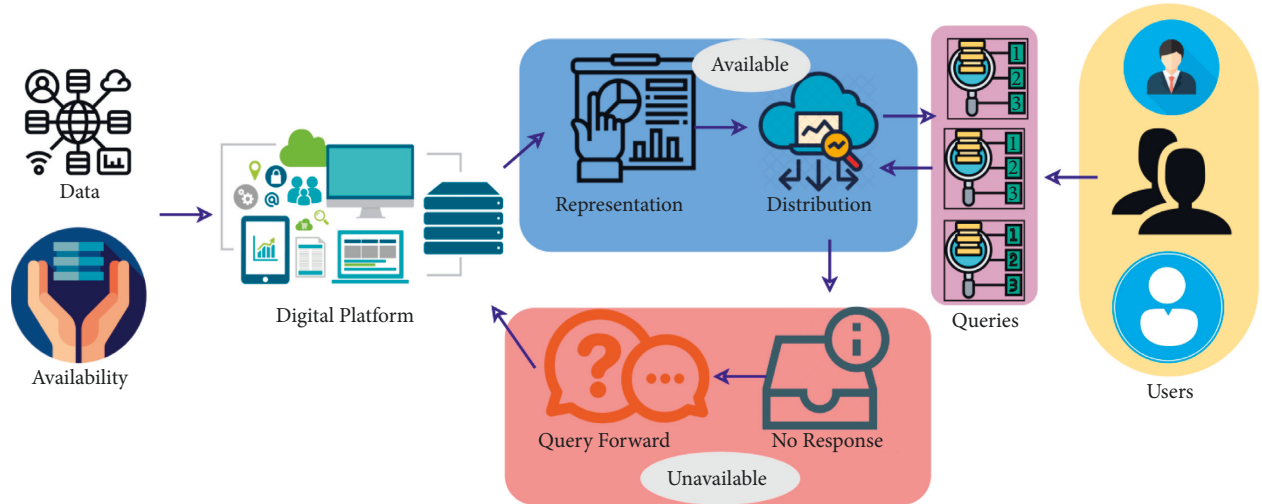


FIGURE 6: Available and unavailable data illustration.

reducing unavailability other than linearly analyzing the services. The pending service in the rural governance is served in this continuous manner, reducing the unavailability. The data between 2016 and 2018 is analyzed for availability and representation as in Figure 5.

The above representation is provided before regressive implication for identifying missing input data. The representation is provided for the data available for the service queries. A formal illustration for differentiating available and unavailable data is presented in Figure 6.

Depending upon the queries and responses, the available and unavailable data are linked to digital platform. The user requests for services are forwarded based on availability and analysis. If the unavailable data is accessed, then the query is forwarded to the service provider. Depending on the availability, the representation is modified due to which the availability chances are high. For the unavailable data, filling from the previous instances is performed for meeting the user demands. The filling is performed using regressive learning, as a sample illustration of data between 2016 and 2018 in Table 2.

The available data is marked as 1 else 0 based on the data set information. The unavailable data is regressed linearly for preventing unnecessary lag in data distribution. Based on Availability ( $n$ ), the regression model is estimated as in Figure 7.

The regressive analysis relies on  $\rho_{L_q}$  and  $f(d)$  for precise data distribution, representation, and analysis. This is required for preventing unavailability based on  $D_{\text{processing}}$ ; it is improved for improving the data availability. The failing regressive processes are recused for cumulative data representations, preventing failures. After the regressive process, the data-related attributes are tabulated in Table 3.

## 4. Results and Discussion

The performance of the proposed method is analyzed using a test case for data representation obtained from [29]. This data source provides food outlets opened between 2016 and

TABLE 2: Data availability between 2016 and 2018.

Year	Name	Services	Human resource	Values	Profit	Loss	Variables
2016	0	1	1	0	0	1	1
2017	0	1	1	0	0	0	1
2018	1	1	1	0	0	1	0

2018 in rural regions of Mississippi. The data representations are projected based on available services; distinguishing distribution and previous data. The dataset contains 8 fields based on installation, commissioning, and running details. With this information, the data analysis and representation are analyzed.

### 4.1. Discussion on Comparative Analysis

**4.1.1. Analysis Time.** In Figure 8, the rural governance depends on population, distinct geographical and fundamental service attributes in digital platform based on artificial intelligence, and big data analysis for deploying operation modes and digital construction are the consideration factor that does not provide continuous data representation at different intervals. The forward regression for data representation and service delegations based on data semantics for the available services and linearity checking for the availability considered for further application-specific user interactions based on service requirements for both the instance  $u \times D_r$  and  $t \times D_r$  in a consecutive analysis of data processing. This availability monitoring analysis is addressed by linearity analysis based on rural governance construction  $P_r \forall i \in D_r$  in the previous survey-based on analysis time and processing, preventing unavailability. Rural governance includes surveying, identifying, and fulfilling the demands that are analyzed based on the user interactions depending on the logical regression analysis that provides data distribution for service requirements and data organization in the digital platform. Based on the unavailability and processing

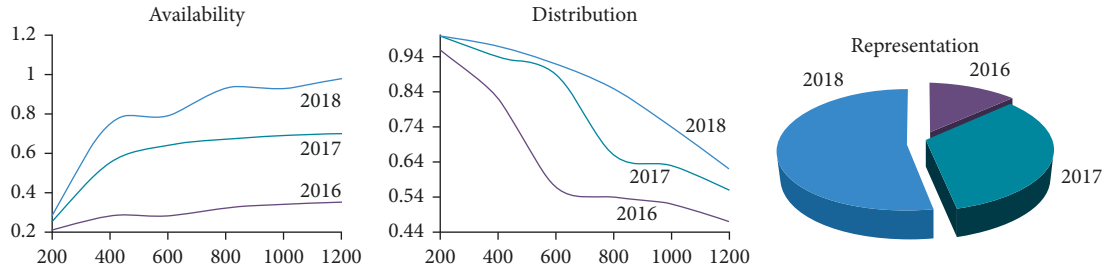


FIGURE 7: Regression model outputs.

TABLE 3: Postregression data features.

Metric	Before			After		
	Availability	Representation	Distribution	Availability	Representation	Distribution
Name	0.3	0.21	0.4	0.58	0.41	0.6
Services	0.32	0.31	0.51	0.62	0.48	0.74
HR	0.41	0.39	0.59	0.59	0.52	0.68
Values	0.52	0.43	0.63	0.65	0.74	0.76
Profit	1	0.74	0.74	1	0.87	0.97
Loss	0.65	0.35	0.89	0.74	0.75	0.84
Variable	0.82	0.69	0.92	0.98	0.82	0.89

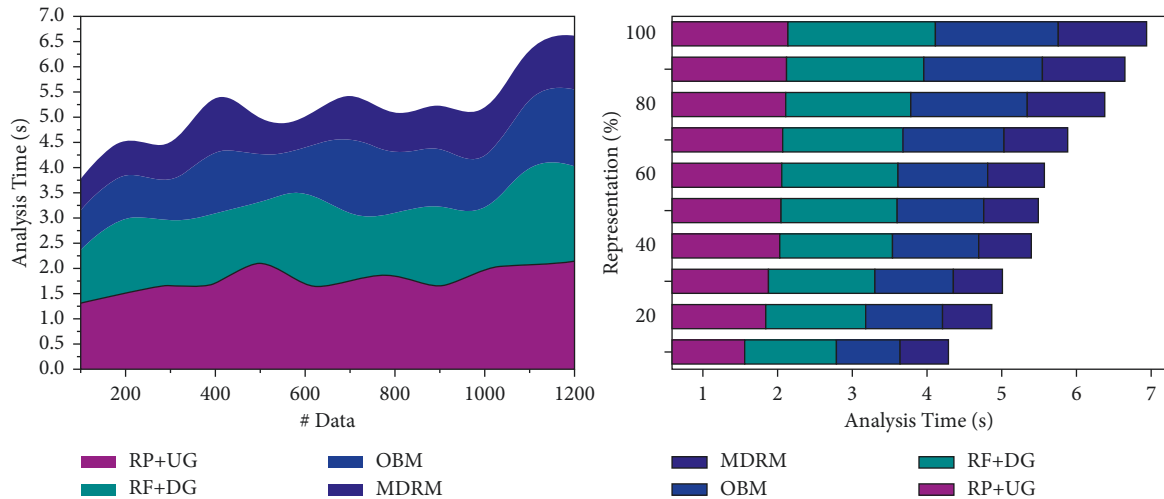


FIGURE 8: Analysis time.

rate in the rural governance, the proposed method satisfies less analysis time.

**4.1.2. Data Processing Rate.** The availability and processing analysis for digital rural governance in big data analysis are represented in Figure 9. This proposed method satisfies fewer data processing rates by computing the service requirements based on application-specific user interactions and fundamental service attributes in the digital platform at different time intervals and fulfilling the user demands and needs. In this unavailability and processing based on discrete data representation, such that  $(1 - D_r \in n/D_r, \in t)$  is performed and reduces the need for additional representation. The proposed method identifies the digital platform implications for mitigating service availability depending upon the data representation and

distribution in a digital platform, wherein the services in rural governance digital platform based on analysis time are preceded using equations (4a)–(7) estimation. This continuous representation processing prevents linearity analysis to forward regression through regression learning based on the unavailability, service-based attributes and requirements and analyzed through regression learning. Based on this consecutive manner of data representation, the analysis time of service delegations is computed at different time intervals.

**4.1.3. Unavailability.** This proposed method augments the analysis, presentation, and interaction in the governance process through requirements-based intelligent processing between analysis time intervals and does not provide data semantics during processing in the digital platform. The computation of

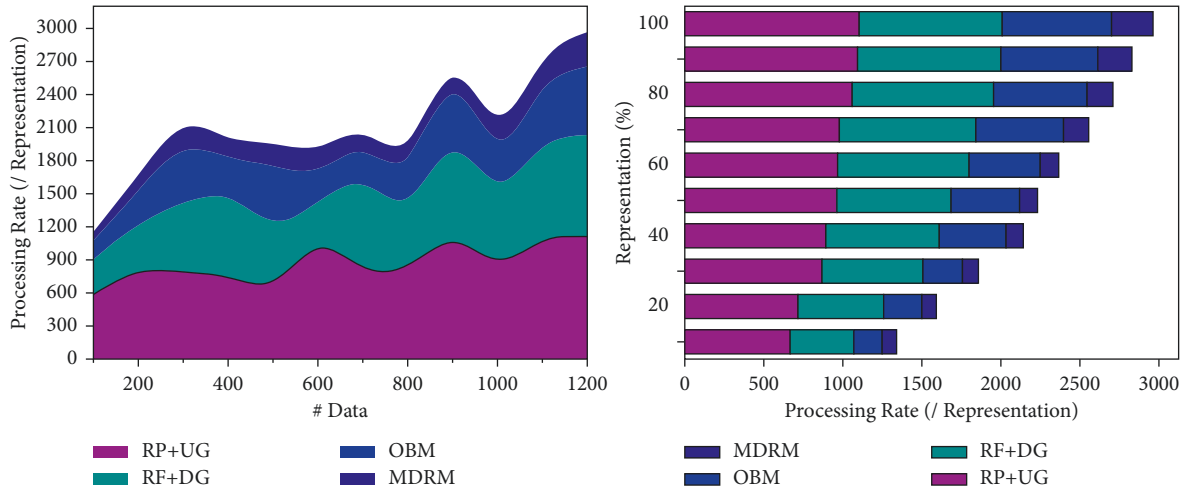


FIGURE 9: Processing rate.

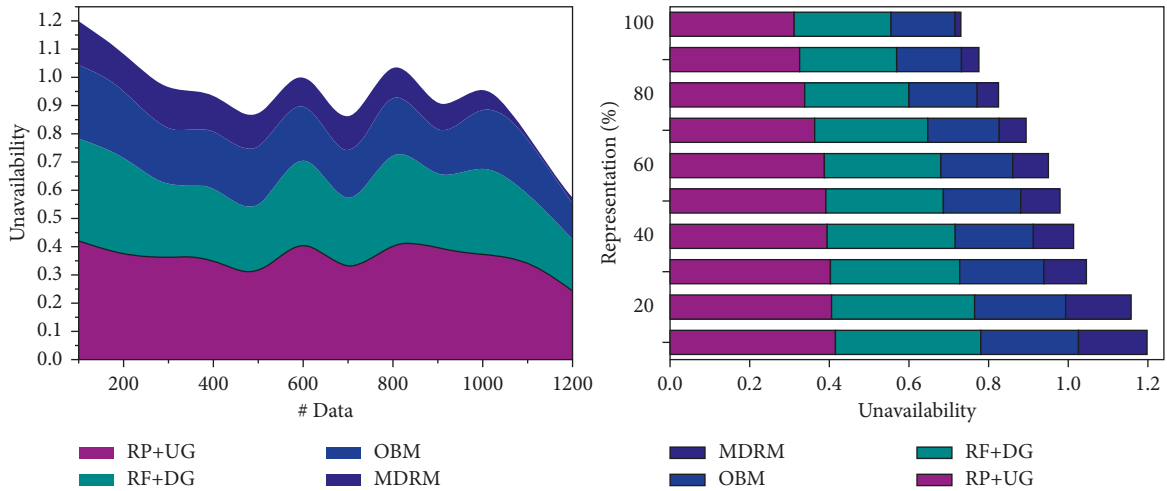


FIGURE 10: Unavailability.

the fundamental service attribute is considering factors based on the data organization and linearity checking based on data representation. Distribution ( $n$ ) is computed using unavailability identification and service delegations for analysis time and data distribution analysis sequence of users and services-based linear and nonlinear data processing can be analyzed for the above condition in the digital platform. Based on the unavailability and service-based attributes, requirements are analyzed through regression learning. The analysis of data representation can be processed in two conditions, namely processing and availability analysis are performed based on the service distribution at a different time interval and then previous regressive output without increasing the analysis time. The proposed method provides linearity analysis based on the service requirements and attributes for which digital rural governance achieves less unavailability as presented in Figure 10.

**4.1.4. Service Delegation.** This proposed method achieves high service delegations for rural governance and the unavailability of big data monitoring based on data

representation at different intervals is aided in identifying the service requirements (refer to Figure 11). The continuous representation analysis and linearity checking are mitigated based on  $u > t$  the rural governance users, and services for analyzing the big data information due to representation recommendation and data-driven analysis in the digital platform through logical regression learning. The service unavailability is due to data representation and service delegations in rural governance applications based on AI and Big Data analysis in a different interval for service unavailability identification for reducing the data processing rate based on the fundamental service attributes observed from the services in both the instances  $D_r = D_d - n$  and  $D_r = D_d$  for available users and services of processing require the previous survey about the services in the rural governance. Therefore, the linearity checking based on Big Data for increasing the data processing rate for verifying linearity depends on considering factors in the digital platform, and therefore, the service delegation is high and service availability also increases. The above comparative analysis is summarized in Tables 4 and 5 for the varying # Data and Representation %

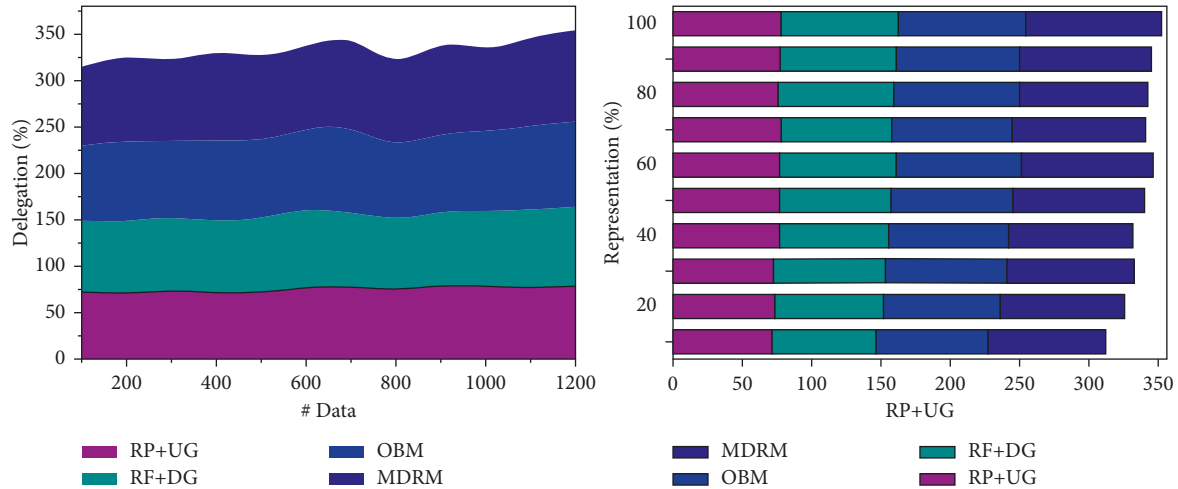


FIGURE 11: Delegation %.

TABLE 4: Comparative analysis summary (varying data).

Metrics	RP + UG	RF + DG	OBM	MDRM	Findings
Analysis time (s)	2.14	1.89	1.52	1.074	6.9% less
Processing rate (/representaion)	1106	921	626	311	10.81% less
Unavailability	0.242	0.182	0.122	0.024	15.8% less
Delegation %	78.52	84.71	92.38	98.508	13.3% high

TABLE 5: Comparative analysis summary (varying representation %).

Metrics	RP + UG	RF + DG	OBM	MDRM	Findings
Analysis time (s)	2.14	1.97	1.64	1.191	6.3% less
Processing rate (/representation)	1103	904	687	270	11.65% less
Unavailability	0.312	0.243	0.161	0.0149	11.19% less
Delegation %	78.28	84.63	91.32	98.044	13.3% high

## 5. Conclusion

This article introduced a modular data representation method for improving the service availability of rural governance on digital platforms. The semantics-based data analysis, distribution, and representation are performed using this method aided by artificial intelligence and digital scenarios. The preprocessed data organization, availability, and linear analysis are aided by regression learning. Based on the availability, the continuous and processing distributions are analyzed for preventing retardations in service delegations. The service requirements are satisfied using diverse representations as deserved from the regressive output. The service distribution is planned based on previous delegations and current data available for ensuring maximum service delegations. This induces improvements in data processing with limited time for different services. For the varying representation ratios, the proposed method achieves 6.3% less analysis time, 11.65% less processing rate per representation, 11.19% less unavailability, and 13.3% high service delegation.

## Data Availability

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

## Conflicts of Interest

The authors declare that there are no conflicts of interest with any financial organizations regarding the material reported in this article.

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