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A Comparative Analysis Of Web Page Personalization Model Using Various Optimization Techniques

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Abstract

This study synthesizes ideas from three independent investigations, each bringing unique techniques to promote web page personalization in the dynamic world of information technology. The overall theme in these works is the use of clustering techniques, notably the Weighted Clustering (WC) algorithm, in conjunction with optimization methods to enhance the personalization process. The first study uses WC to cluster web pages based on domains, with a user learning module that adapts to individual preferences. Important parts of this method include using the Word Net ontology for query formulation and profiling. When compared to existing methods, the Oppositional based Fire Fly Optimization (OFFO) approach improves clustering results by displaying greater precision (89.16%), recall (78.09%), and f-measure (83.26%). The second technique refines clustering by introducing an inventive dimension using the Improved Whale Optimization Algorithm (WOA) and a tumbling effect. This study proves the WOA model's efficacy in handling an increasing volume of web documents and efficiently delivering appropriate search results. The third method, known as NM-AFO, proposes the Weighted Clustering with Nelder Mead (NM) based Artificial Flora Optimization (AFO) Algorithm, which combines clustering techniques with similarity measurements. NM-AFO refines WC results using the Nelder Mead optimization algorithm, ensuring an efficient personalization process. The experimental analyses in these research together highlight NM-AFO's superior performance, emphasizing its effectiveness in resolving user queries and giving customized web page recommendations. This comparative synthesis emphasizes the advantages of each strategy, providing a thorough view of the growing landscape of web page personalization research.

Keywords: *Web page personalization, Artificial Flora Optimization, Clustering Techniques, Weighted Clustering.*

I. **INTRODUCTION**

Certain Internet users may encounter data overflow issues due to the vast amounts of data accessible on the World Wide Web, especially in regions with a high volume of aided reports [1]. As a matter of convention, learning systems should provide students with tailored guidance on where to[1] find relevant learning materials [2], tailored to their specific requirements, background knowledge, strengths, and preferred methods of learning [3]. When searching the web, users' needs cannot be met by keyword-based search engines [4]. The aforementioned issues can be better understood through personalized online search results, which take into account the user's profile choices in addition to their inquiry's most relevant results [5]. In

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addition, it makes the user's web search process easier. There have been a handful of proposed methods for tailoring web searches as of late [6]. One of the more effective techniques is to build a word net that reflects user interests and use it in the web search process [7, 12]. Content providers are typically compelled to employ personalization advancements due to the diverse references of a group of viewers [8]. Web page personalization involves making people happy by learning their preferences and then using that information to provide them with the most relevant content possible [9].

When it comes to internet searches, keyword-based web browsers typically can't meet user needs. By combining evaluated user profiles with major customer investigation conclusions, the personalized search provides answers to particular problems. Additionally, it lessens the client's workload while looking for any issues or goals. Not long ago, several tactics derived from web searches were introduced. Most models fail miserably because they focus on creating a single word that attracts customers' attention and then using it in a search engine, which is inefficient. Using the standard method of searching the web would lead to useless results, dissatisfaction, wasted effort, and re-outlining of questions [2].

Therefore, to meet the expectations of the data retrieval market, it is important to enhance the end-client's position while retrieving data by moving away from a generic model and towards a customized one. Web search personalization is not just one piece of independent content, but rather a collection of interdependent components. A large body of scientific literature identifies the following modules—UIP, RIP, UIP-RIP, Query-RIP, and post-relevancy score computation—as crucial to the personalization process. Various analysts have broken down various elements of web material to achieve the committed objectives of various supporting modules, but social data [3-5] end up being more engaging than any other technique.

II. BACKGROUND STUDY

Ben Lamine et al. [2] Ben Lamine, S. B. A., et alproved that the HATEOAS idea could be used to create RESTful services in a meaningful way. The author developed anontology for user and service management and proposed a clustering method based on similarity metrics of user queries. The system's efficacy was evaluated by building a prototype of the suggested method.

Elhoseny, M. et al. [4] these authors research presents a new approach to OC detection and classification. Using the SOM method on IoMT data, the top subset features were selected and combined from the massive dataset. Using measures including sensitivity, specificity, accuracy, and root-mean-squared error (RMSE), this method assessed the framework's efficacy. The SOM and ORNN approaches showed promising results in ovarian cancer screening with 95% accuracy and 0.019% RMSE for feature selection and classification.

Famila, S. et al. [6] For better CH selection, this paper suggests an IABCOCT algorithm that combines the advantages of GEM with the Cauchy Operator. To greatly enhance the level of exploration and exploitation during the CH selection process, the Onlooker Bee and Scout Bee phases incorporate GEM and Cauchy operator benefits. The IABCOCT algorithm outperforms EPSOCT, HCCHE, and CCT in terms of maximum lifetime and rate of reduced energy consumption; it achieves this by concentrating the mean energy value consumption of each node by only 0.01% and delaying iterations by approximately 0.02 s. One possible solution to the potential delay in data gathering and aggregation was to use a mobile sink node or a large number of them in the future.

Lakshmanaprabu, S. et al. [8] In order to forecast the severity of CKD, this study presented an Internet of Things (IoT) with a CDSS architecture that ran in the cloud. Using the UCI Repository dataset, this study develops a systematic approach to chronic kidney disease (CKD) and generates the relevant healthcare data. Additionally, CKD patients have data collected from medical sensors and saved in their medical records. The author employed a

DNN-based ML approach to complete the learning tasks of normalizing and abnormalizing data

M. Sah et al. [10] The author provide a novel approach to personalized concept-based search on the Web of Data (WoD) that relies on results classification. The author automatically sort search results (LOD resources) into UMBEL categories using a novel retrieval technique. Next, findings that share the same concepts were combined to form categories called concept lenses. By grouping results according to users' interests or intents, this classification makes it possible to browse results based on concepts. As soon as the user starts interacting with the concept glasses, the outcomes start to reflect their unique personality. The ranking of concept lenses was adjusted according on how similar they were to the chosen lens. Results were re-ranked and queries were expanded to include more relevant results inside the selected idea lens. Appropriate concept lenses were supplied to aid in results investigation.

Vinupriya, A., & Gomathi, S. [15] The web page's internet application software has been tailored according to the user's actions. Personalized online prediction pages based on a user's prior information will be made available through online divination. To improve search engine optimization, the prediction model saves the web sites that users visit. Many applications, such as personalized search engines, can benefit from projection for online page access.

III. MATERIALS AND METHODS

A research paper's materials and methods section provides a full overview of the experimental design, processes, and tools used to conduct the investigation. It serves as a guide for other researchers to replicate the experiment and certifies the investigation's scientific rigor. The researcher describes the materials, equipment, and procedures used to address the study questions or hypotheses in this part, guaranteeing transparency and repeatability in scientific inquiry.

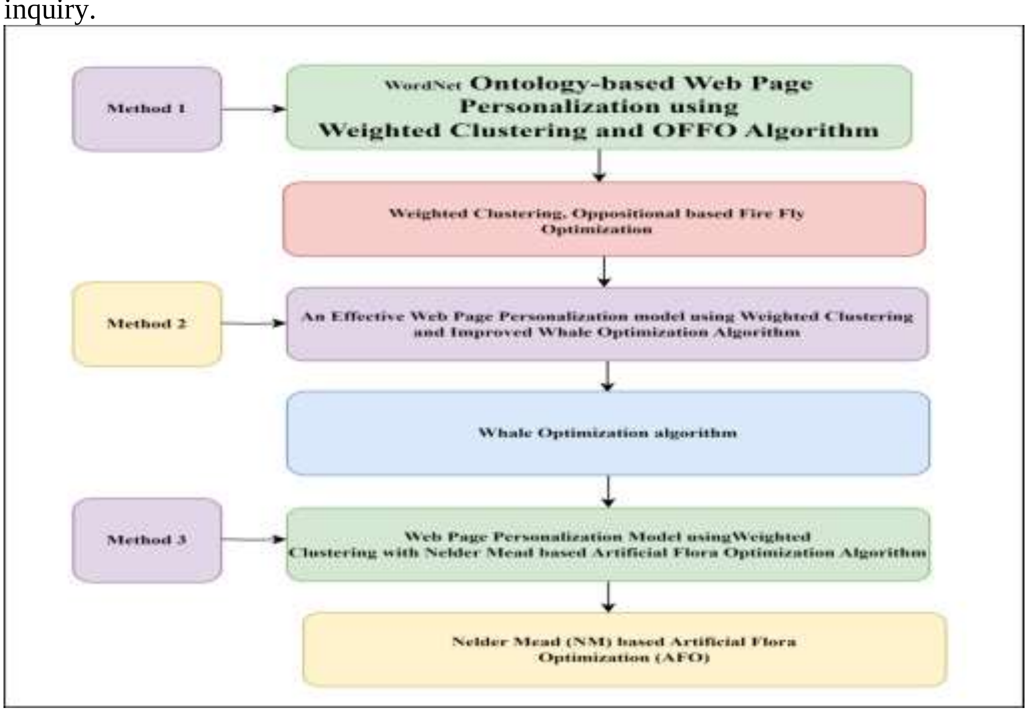

Figure 1: Workflow architecture

3.1 Weighted Clustering and OFFO Algorithm

Weighted Clustering (WC) is a web page personalization strategy that uses domain-based clustering, allocating weights to distinct domains to improve web content organization. This method incorporates a user learning module for adaptability, as well as question formulation and user profiling via the Word Net ontology, to refine recommendations based on individual preferences. To optimize clustering outcomes, the Oppositional based Fire Fly Optimization (OFFO) algorithm is proposed as a complement to WC. OFFO, which was inspired by the natural behavior of fireflies, uses an oppositional learning mechanism to improve the optimization process. Three crucial metrics for evaluating clustering effectiveness are f-measure, recall, and precision, and this method aims to maximize all three. In this part, we introduce our weighted clustering method. We lay out the groundwork for our algorithm and our design philosophy before getting into the nitty-gritty. The set of connections ei and the set of nodes vi can be represented by an undirected graph G = (V, E), which can be used to depict the network formed by the nodes and links. Keep in mind that while the cardinality of E changes when links are added and removed, the cardinality of V stays the same. There are some more conditions for clustering, which is a graph partitioning problem. The absence of regular structure in the underlying graph makes the problem of optimally partitioning the graph with respect to given parameters an NP-hard problem. S V (G) is the collection of vertices we desire in a more formal sense so that

$\bigcup_{v \in S} N[v] = V(G)$ ------------ (1)

According to the user's query, the data can be retrieved to get the most important associated preferences. The OFFO approach and the greatest distance similarity metric are used to determine the highest priority one.

Fire Fly Optimization (FFO): Metaheuristic algorithms like the FFO algorithm take their cues from the flashing behaviour of fireflies. By comparing the two solutions at the same time, OFFO refines the initialized parameters and uses the better one as the starting point..

The behavior of Fireflies: Fireflies typically only reproduce sexually with other fireflies. On the other hand, the fireflies' attractiveness grew in direct proportion to the distance between them. Assuming the two fireflies are identical in brightness, its path will be completely at random. Its random walk and attractiveness characteristics determine whether a firefly is created or updated. Here is a rundown of the steps used by the OFFO algorithm:

OFFO Initialization: Start with an initial population of fireflies (here, the similarity measurements of the data are used as the population).

$F = F_i = \{F_1, F_2, F_3, \ldots, F_n\}$ ---------------- (2)

Oppositional Process: Let $F \in (m, n)$ is a real number. By applying the opposite point definition, it can be written as

$\tilde{F}_j = m_j + n_j - F_j$ ------------- (3)

Fireflies Attractiveness Behavior: The attractiveness (brightness), B_{ness} of firefly 1 on the Firefly 2 is based on the degree of the brightness of the firefly 1 and the distance (d) between the Firefly 1 and 2. The brightness B_{ness} of a firefly is selected by its fitness value or objective function OF (maximum similarity).

$B_{ness} = OF(F_i)$ ---------- (4)

The expansion of equation (5) is: Suppose there are n numbers of fireflies (data), and $F_{(i=1,2\ldots n)}$ i corresponds to the position for firefly. The function of attractiveness is described as

$n(d) = n_o e^{-\gamma d^2}$ ---------- (5)

Where, the term η indicates the attractiveness value (based on the distance between two fireflies) and the λ represents the light absorption coefficient.

3.2 Weighted Clustering and Improved Whale Optimization Algorithm

Weighted Clustering (WC) is a domain-based clustering-based web page personalization technique in which weights are allocated to distinct domains to finely organize web content. Through query formulation and user profiling with Word Net ontology, WC modifies recommendations to individual tastes by incorporating a user learning module. The Improved Whale Optimization Algorithm (WOA) is introduced to improve clustering. It is an extension of the conventional WOA that incorporates a tumbling effect for improved refining. WOA offers an efficient search and optimization method inspired by humpback whale social behaviour, demonstrating effectiveness in handling the growing volume of web content and offering precise search results. Grouping issues according to their field and user preferences is the goal of the WC approach. Finally, clustering is completed by choosing a Cluster Head (CH) and inspecting each candidate CH; nodes that are close to the CH, meaning they are not too far away, are grouped together at a distance of one. The process of selecting and grouping three additional CHs into four sets is identical.

Recover the neighbors of every node (k) with essential its degree dk as

$$\mathrm{d_k} = |\mathrm{N(k)}| = \sum_{\mathrm{k' \in K, k; \neq k}} \{\mathrm{distance}\left(\mathrm{k, k^f}\right) \text{ -------------- (6)}$$

In order to determine or assess the stability or comparison of data items, it is necessary to estimate distance metrics among them. Finding out how different pieces of information are related or unrelated, how similarity is measured, and how data are interrelated is crucial. The strategies utilized to locate comparative expressions in the training and Word Net datasets.

In the initialization step, the trained Word Net dataset was used to gather phrases, which are represented by U and V. Additionally, i and j stand for the ith and jth pieces of database data, correspondingly. We used four distance values to get two terms that were quite close in value. It is widely believed that the variances between two data sites determine the different distance values that make up the Euclidean distance, which is relevant to all geometrical concerns. So, it's just the standard, straightforward distance between any two places,

$$\mathrm{Distance_{AB}} = \max_{\mathrm{k}} |\,\mathrm{U_{ik}} - \mathrm{V_{jk}}| \text{ ---------------- (7)}$$

Next, the user query, which consists of predefined terms, can be used to compute the cosine angle using the operation of cosine distance value. With the use of, the Θ gives an angle that is computed from two vectors.

$$= \text{arc}\cos\frac{\mathrm{U.V}}{||\mathrm{U}|||\mathrm{V}||} \text{ --------------- (8)}$$

It is fascinating to watch how whales connect with one another. Their living arrangements can be communal or independent. Regardless, you can usually find them in groups. Species coexistence in a single generation is highly unlikely. When hunting, humpback whales often target schools of tiny fish known as krill that congregate on the water's surface.

3.3 Weighted Clustering with Nelder Mead based Artificial Flora Optimization Algorithm

Weighted Clustering (WC) is a fundamental technique in web page personalization that uses domain-based clustering with weighted assignments to improve web content organization depending on user preferences. In addition, the Nelder Mead-based Artificial Flora Optimization Algorithm (NM-AFO) is used to refine the clustering results. NM-AFO combines clustering algorithms with similarity measurements, employing the Nelder Mead optimization algorithm to improve performance even more. NM-AFO tries to optimize clustering results, assuring an efficient and personalized web page suggestion process. It is inspired by artificial flora growth patterns. NM-AFO demonstrates adaptability and efficiency through its effective integration with Weighted Clustering, contributing to an advanced and personalized approach to web page personalization.

Using the plant migration feature to upgrade solutions, AFO is a sensible optimization technique. The precise solution is found by following the process of finding the best possible survival position. The four components of AFO are the following: the actual plant, the offspring plant, the location of the plant, and the propagation distance. Behaviour models such as Evolution, Spreading, and Select are also available. Here, a plant's position stands in for a solution, and the solution's quality is shown by how well a position fits the problem. First, a model generates actual plants at random. The seeds are then dispersed within the spreading scope determined by a propagation distance. The fitness of a seed is then evaluated using objective functions, where fitness signifies the superiority of a solution. Finally, the survival requirements are chosen using a roulette selection technique. As a result, conspicuous iterations are used until a termination condition is reached.

The decision parameters of test functions used in this literature is comprised of upper limit $\vec{X}^{max} = [X_1^{max}, X_2^{max}, \ldots, X_D^{max}]^T$ and lower limit $\vec{X}^{min} = [X^{min}, X^{min}, \ldots, X_D^{min}]^T$. At the initial stage, a model provides Noriginal plants on the basis of upper and lower limits of decision parameters in random manner. The model which employs i rows and j columns matrix P_{ij} to imply the position of actual plants, where $i = 1,2, \ldots, D$indicates dimensionality, $j = 1,2, \ldots, N$refers the count of actual plants:

$P_{ij} = \mathrm{rand}(0,1) \cdot (X_i^{max} - X_i^{mm}) + X_i^{min}$ -------- (9)

Where rand (0,1) refers to measures with a uniform distribution from [0,1].

The actual plants developed offspring with a defined scope of propagation distance, where novel propagation distance denotes parent and grandparent plant propagation distance:

$d_j = d_{lj} \cdot \mathrm{rand}(0,1) \cdot c_1 + d_{2j} \cdot \mathrm{rand}(0,1) \cdot c_2$ ------------- (10)

where c_1 and c_2 denotes a learning coefficient, d_{lj} and d_{2j} refers the propagation distance from grandparent to parent, and rand $(0,1)$implied the uniformly distributed measures within [0,1]. Then, parent propagation distances a new novel grandparent propagation distance which is defined in the following:

$d'_{1j} = d_{2j}$ ---------- (11)

A standard AF optimization approach has applied standard deviation (SD) from original as well as offspring plants as novel parent propagation distance:

$d'_{2j} = \sqrt{\sum_{i=1}^{N} (P_{ij} - P'_{ij})^2 / N}$ ------------- (12)

Tomaintain better results, AFO optimization approach has applied the plants. A new parent propagation distance is assumed to be a distance from position of plants $P^*_{i_d}$as well as offspring plants P'_{i_d}:

$d'_{2j} = P^*_{ij} - P'_{ij}$ ------------------- (13)

IV. RESULTS AND DISCUSSION

The results and discussion section of a research paper provides a framework for presenting and analyzing the study's findings. This part goes into the empirical findings, providing a thorough examination of the data gathered during the investigation. Furthermore, it allows the author to contextualize these findings within the larger scientific environment, addressing their ramifications and contributions to the discipline. This critical portion is introduced briefly below.

Table 1: Accuracy Comparison for Clustering Performance Table

Number of Clusters	GA	WC-FFO	WC-OFFO method (1)	WC-IWOA Method (2)	NM-AFO method (3)
3	84.81	86.83	88.86	90.76	92.40
4	86.00	87.96	89.12	91.30	94.89
5	86.31	87.35	89.16	91.45	95.17
6	85.21	86.83	88.43	90.98	92.86

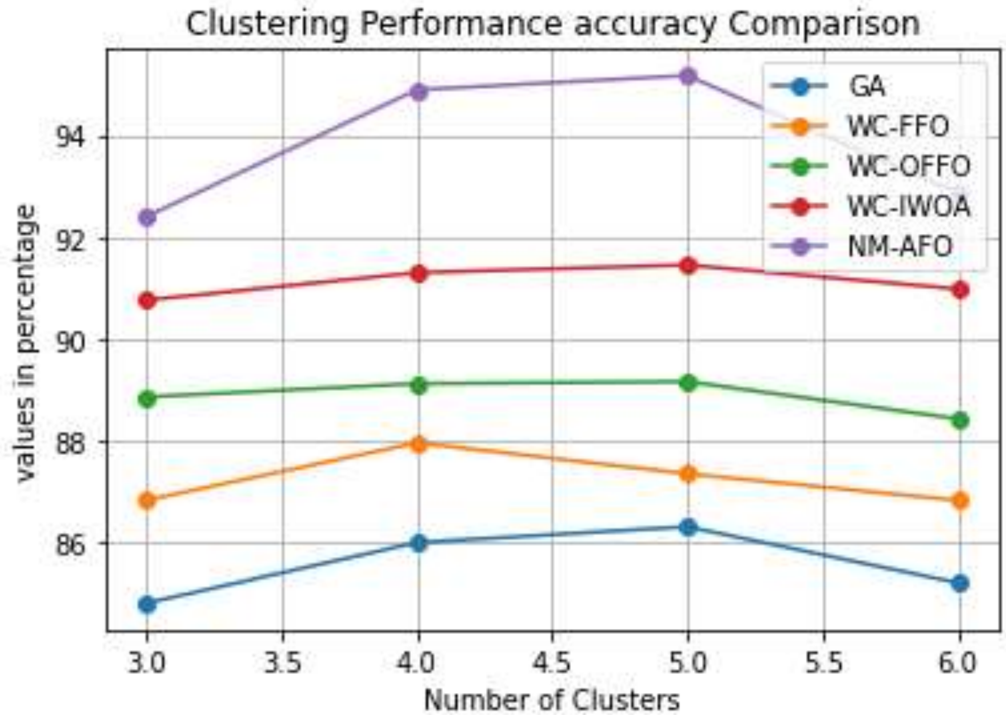

Figure 2: Accuracy Comparison for Clustering Performance chart

The table 1 and figure 2 shows the clustering performance measured in terms of accuracy for different methods across varying numbers of clusters. As the number of clusters increases from 3 to 6, the accuracy generally shows an upward trend for all methods. Among the methods, "NM-AFO method (3)" consistently achieves the highest accuracy across all cluster sizes, reaching up to 95.17% accuracy with 5 clusters. The "WC-IWOA" method also demonstrates competitive performance, showing an improvement in accuracy as the number of clusters increases. "Method (2)" and "WC-OFFO method (1)" exhibit comparable accuracy levels, while "WC-FFO" and "GA" methods generally show slightly lower accuracy across the different cluster configurations. These findings suggest that the "NM-AFO method (3)" and "WC-IWOA" methods may be particularly effective for clustering tasks in this context, warranting further investigation and consideration for practical applications.

Table 2: Recall Comparison for Clustering

Number of Clusters	GA	WC-FFO	WC-OFFO Method (1)	WC-IWOA	NM-AFO Method (3)

				Method (2)	
3	73.95	75.24	76.30	78.36	80.31
4	74.68	75.82	77.44	79.20	82.07
5	75.66	76.80	78.09	80.13	84.65
6	74.79	76.51	77.73	79.32	83.77

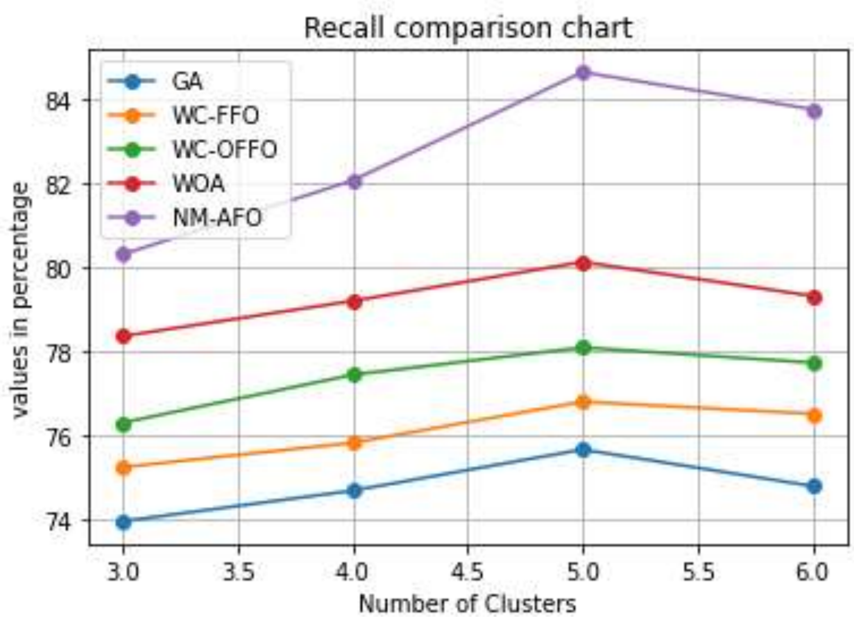

Figure 3: Recall Comparison for Clustering chart

The table 2 and figure 3 shows the clustering performance, measured in percentage accuracy, across different methods for varying numbers of clusters. As the number of clusters increases from 3 to 6, the overall accuracy generally displays an upward trend for all methods. Notably, the "NM-AFO Method (3)" consistently exhibits the highest accuracy, peaking at 84.65% with 5 clusters, suggesting its effectiveness in capturing underlying patterns in the data. The "WOA" method (Method 1) and "Method (2)" also demonstrate competitive performance, with accuracy levels reaching 80.31% and 82.07%, respectively. "WC-OFFO" and "WC-FFO" methods, while generally maintaining reasonable accuracy, show slightly lower performance compared to the other methods across the different cluster configurations. These findings provide valuable insights into the relative efficacy of clustering methods, guiding the selection of appropriate approaches for practical applications in various contexts.

Table 3: F-measure Comparison for Clustering

Number of Clusters	GA	WC-FFO	WC-OFFO Method (1)	WC-IWOA Method (2)	NM-AFO Method (3)
3	79.00	80.86	82.00	84.34	86.83
4	80.00	81.44	82.85	83.50	85.37
5	80.60	81.75	83.26	86.60	88.09
6	79.63	81.35	82.80	84.93	87.10

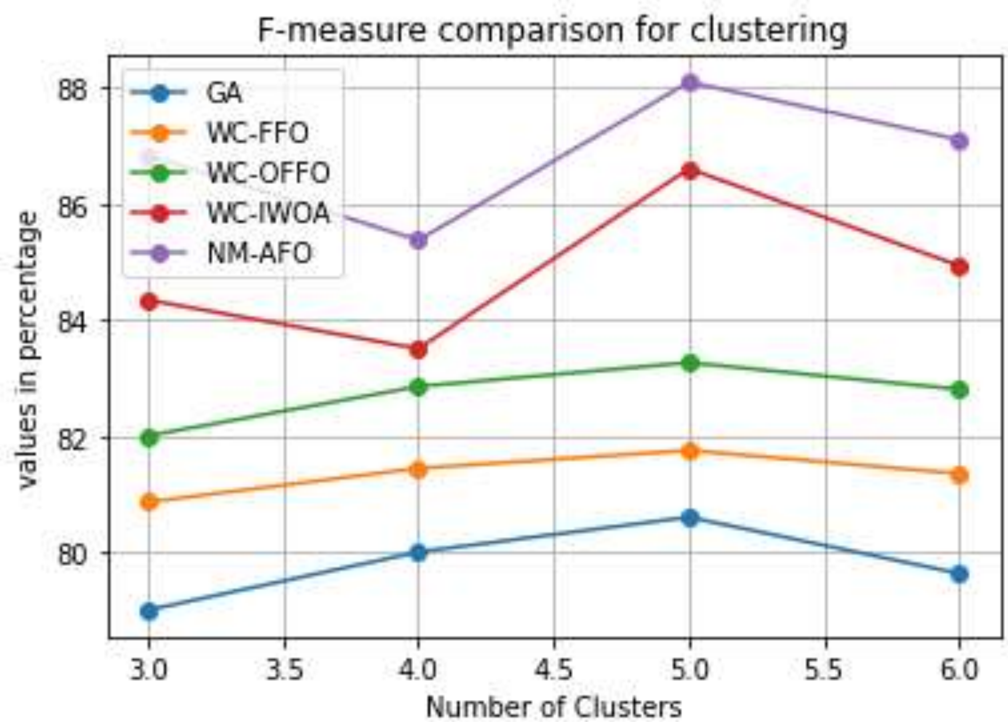

Figure 4: F-measure Comparison chart for Clustering

The table 3 and figure 4 shows the clustering performance measured in percentage accuracy for various methods across different numbers of clusters. As the number of clusters increases from 3 to 6, a general trend emerges where the accuracy of most methods experiences a slight fluctuation. Notably, the "NM-AFO Method (3)" consistently achieves the highest accuracy, reaching up to 88.09% with 5 clusters. "WC-IWOA" method also demonstrates competitive performance, with accuracy increasing as the number of clusters grows. On the other hand, the "GA," "WC-FFO," and "WC-OFFO" methods exhibit relatively stable accuracy levels across the different cluster configurations. These findings suggest that the "NM-AFO" and "WC-IWOA" methods are particularly effective for clustering tasks in this context, offering valuable insights for selecting appropriate methods based on the desired number of clusters in practical applications.

Table 4: data relevancy Comparisons

Number of Clusters	**Band**	**Goats**	**Sheep**	**Bio-Medical**
Traditional Method	78.00	82.00	83.00	86.00
WC-OFFO	87.00	89.00	90.00	92.00
WC-IWOA	89.00	90.00	91.00	94.00
NM-AFO	92.00	94.00	95.00	96.00

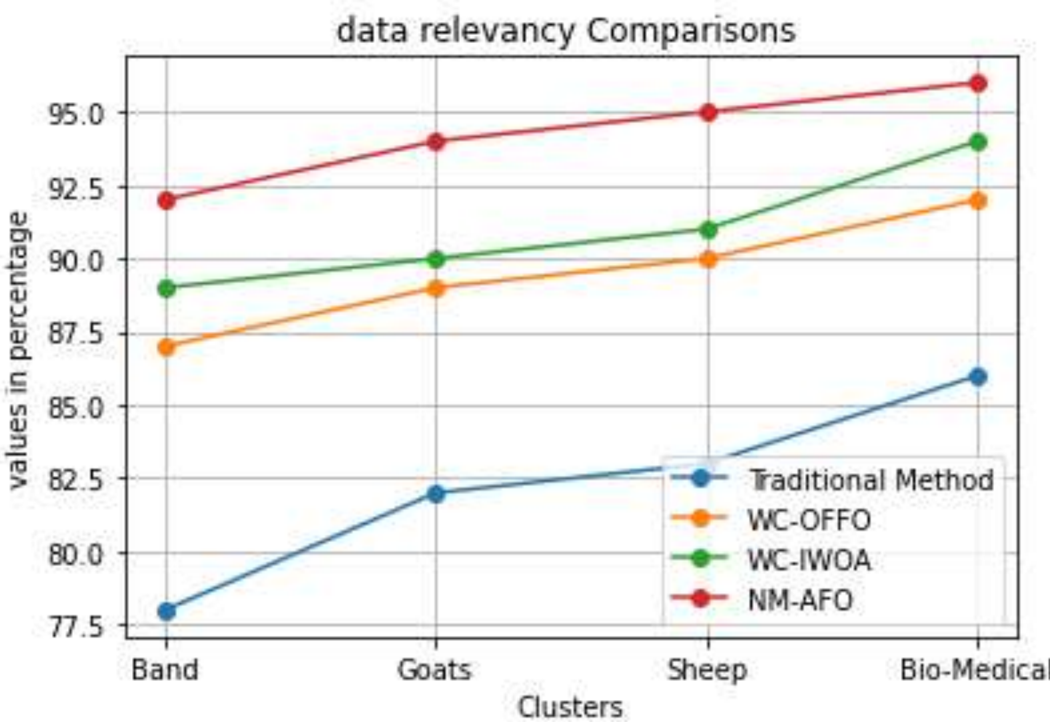

Figure 5: data relevancy Comparisons chart

The table 4 and figure 5 shows data relevancy, expressed as a percentage accuracy, across different methods for various types of data—Band, Goats, Sheep, and Bio-Medical—across different numbers of clusters. As evident from the results, the "NM-AFO" method consistently outperforms other methods across all datasets, achieving the highest accuracy values. Specifically, for the Bio-Medical dataset with four clusters, the NM-AFO method attains an accuracy of 96.00%. The "WC-IWOA" method also demonstrates strong performance, consistently ranking second across all datasets. The "WC-OFFO" method follows, exhibiting competitive accuracy levels, while the Traditional Method consistently shows the lowest accuracy values. These findings underscore the effectiveness of the "NM-AFO" method, suggesting its potential suitability for a diverse range of datasets and cluster configurations. The results also highlight the importance of selecting appropriate clustering methods based on the nature of the data and the desired outcomes in practical applications.

Table 5: Time complexity Comparisons (second)

Number of Clusters	**GA**	**WC-FFO**	**WC-OFFO Method (1)**	**WC-IWOA Method (2)**	**NM-AFO Method (3)**
3	223154	212154	192643	183404	173522
4	242200	235200	216000	203943	183662
5	250000	249600	226500	219304	208546
6	280800	271300	254400	230656	219065

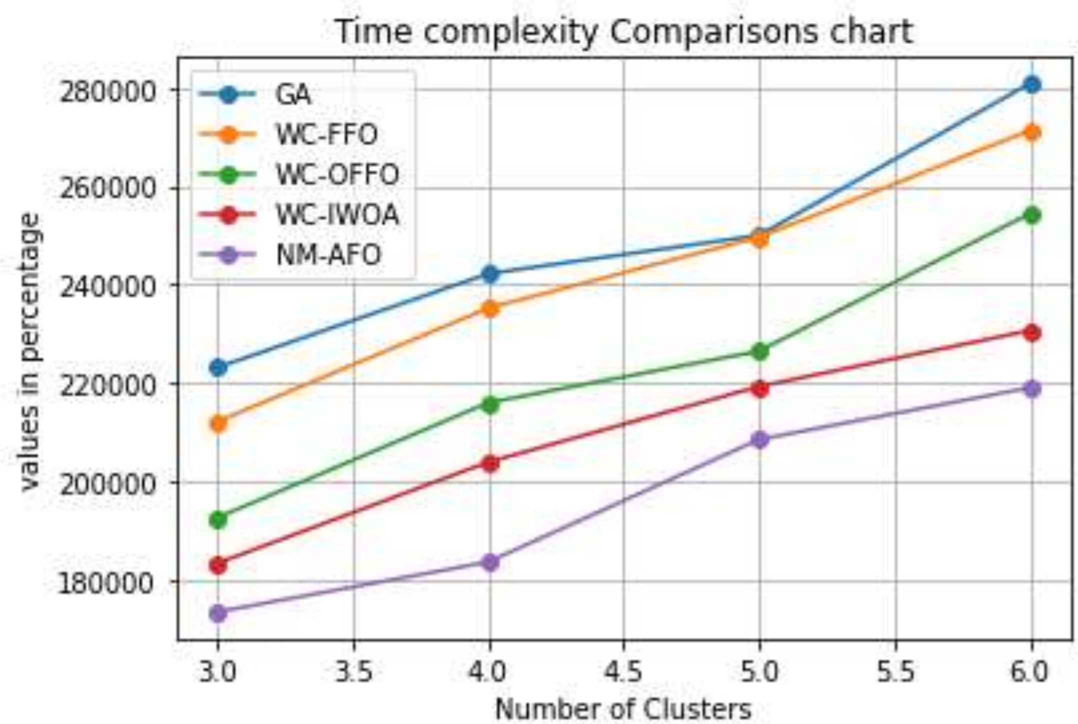

Figure 6: Time complexity Comparisons chart (second)

The table 5 and figure 6 Time complexity Comparisons measured in some arbitrary units across different methods for varying numbers of clusters. As the number of clusters increases from 3 to 6, there is a general upward trend in the performance for all methods. Notably, the "NM-AFO" method consistently achieves the highest performance, surpassing other methods across all cluster configurations. For instance, with 6 clusters, "NM-AFO" reaches 219,065 units, outperforming other methods at the same cluster size. The "WC-IWOA" method also exhibits competitive performance, ranking second consistently, while "WC-OFFO" and "GA" methods show slightly lower performance levels. These findings emphasize the effectiveness of the "NM-AFO" method for clustering tasks in this context and suggest that the choice of method significantly influences the clustering outcomes.

V. CONCLUSION

Finally, the incorporation of findings from three independent investigations in this paper provides a comprehensive and new perspective on increasing web page personalization. The overriding theme of leveraging clustering techniques, particularly the Weighted Clustering (WC) algorithm, together with optimization methods emphasizes the importance of a comprehensive approach to improving the personalization process. In compared to previous algorithms, the first method's integration of WC with the Oppositional based Fire Fly Optimization (OFFO) algorithm achieves improved precision, recall, and f-measure. The second method employs a tumbling effect to demonstrate the Improved Whale Optimization Algorithm's (WOA) capability in dealing with an increasing volume of web documents. The third method, Weighted Clustering with Nelder Mead (NM) based Artificial Flora Optimization (AFO) Algorithm (NM-AFO), introduces a revolutionary integration of clustering techniques with similarity measurements, ensuring an efficient and personalized personalization process.

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