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Fuzzy Logic-Based Clustering of Teacher Digital Pedagogy Using Cybergogy Framework for Sustainable Educational Innovation

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Abstract. Rapid changes in educational technology necessitate innovative approaches to sustainable teacher development. However, implementing learning technologies like Cybergogy faces significant challenges due to imbalances in digital pedagogy competencies and motivation among secondary school mathematics teachers. This study aims to cluster mathematics teachers' profiles based on the Cybergogy model's application using the Fuzzy C-Means (FCM) algorithm. The study involved 88 mathematics teachers from various secondary schools in Yogyakarta, Indonesia. Clustering results converged at the sixth iteration with an objective function value of 620.006, and an optimal two-cluster structure (PCI = 0.5578). Cluster 1 comprises teachers with high digital competencies and effective use of online learning media in understanding Cybergogy. Conversely, Cluster 2 includes teachers with limited online learning experience and low Cybergogy understanding. These findings highlight the lack of appropriate training efforts to support technology implementation and motivate each cluster based on their unique perceptions of Cybergogy. This study contributes to educational technology by offering insights into how the Cybergogy model can enhance digital learning quality, with long-term implications for teacher competency development and the sustainability of digital education innovation in Indonesia.

Keywords: Cybergogy, Fuzzy C-Means, PCA, Digital Pedagogy, Teacher Profiling

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1. Introduction

Cybergogy as a model is conceived as a holistic model for online learning to harmonize cognitive, affective, and social aspects of learning in education process. Wang and Kang [1] originally conceived the Cybercogpy theory as a full-bodied model that goes beyond the traditional pedagogy for including virtual learning environments for better engagement and knowledge construction. In mathematics education it is useful particularly when abstract concepts are able to be transformed into a physical form. The Cybergogy model that includes cognitive, affective and social aspects in digital learning, is very significant to the attainment of the United Nation's Sustainable Development Goals (SDGs). More so SDG 4; taking action on inclusive and equitable quality education and lifelong learning for all. SDG 4 is the one that will guarantee an education for everyone, regardless of certain circumstances (as in, gender of the individual, the income of the family). Cybergogy, supported by digitalization in learning processes, is instrumental in achieving this objective by making new models of access to education possible for groups that were traditionally excluded, such as learners living in marginalized and remote communities, or people with physical disabilities [2].

With the utilization of digital technology, Cybergogy establishes an enriched learning environment with effective engagement of diverse categories of learners who can participate in synchronous and asynchronous learning. The model also stresses developing social and emotional skills in students as they prepare for the fast-changing, digitized work world. In this sense, Cybergogy contributes to the lifelong learning so needed to face the challenges of the digital society, described in SDG 4, where the life skills need to be reinforced as we grow older [3]. Furthermore, Cybergogy addresses digital inclusion objectives by fostering digital skills in both students and teachers. Digital inclusion – a part of SDG 4 – focuses on bridging the digital divide, existing inequalities in access to technology and in the capability of its use effectively for educational purposes. It is essential to have solid footing in cybergogy to make sure all learners are afforded equitable learning opportunities in technology, as it is used to support current learning, and to prepare learners for the workforce that has become more and more dependent upon technology [4]. Thus, the implementation of is not only aligned with but also reinforces the achievement of SDG 4 by ensuring more equitable and technology-based education that is inclusive.

Harasim [5] examined the evolution of online learning theories. She then positioned Cybergogy as a response to customary pedagogical approaches' limitations in digital environments. The author stressed how Cybergogy's strength lies within its holistic approach for learning, which has particular relevance within mathematics education where conceptual understanding, procedural fluency, and problem-solving skills must each be developed simultaneously. Recent research by Sharma [6] looked into the implementation of Cybergogy principles in mathematics classrooms, as well as found meaningful improvements in student engagement as well as in achievement when teachers did effectively integrate digital tools with appropriate instructional strategies. From the 215 secondary mathematics classrooms visited in the study, the authors found that teachers who implemented Cybergogy principles with their mathematical content showed a greater take up for, and adaptability of, the technological pedagogical content knowledge (TPACK) construct in their teaching.

Likewise, Mailizar et al. [7] conducted a comprehensive research on mathematics teachers' readiness for online learning at the time of COVID-19. According to their results, the level of teachers' digital competencies was varying and needs based on the current level were raised for professional development. The findings of this study highlight the need for teacher differentiation in order to support technology integration in mathematics education..

1.1. Teacher Segmentation and Profiling

Teacher segmentation is a helpful method for learning about the different needs and qualities of teachers. In 2017, Prestridge looked at how good teachers are with digital stuff. They found that teachers have different ways of using technology and teaching, innovators, integrators, hesitant, and non-users. This text explains how teachers use technology in various ways and what kind of help they might need.

Tondeur and others [8] studied how teachers' ideas about teaching and using technology are connected. Their investigation unveiled substantial associations between constructivist instructional ideologies and novel technological application. Authors contended that proficient teacher enhancement schemes ought to factor in educators' current convictions and actions, advocating for the merit of partitioned strategies in crafting precise interventions.

Thurm and Barzel [9] executed a prolonged investigation into the evolution of educators' proficiency in the use of digital tools within the realm of mathematics instruction. They recognized unique developmental pathways and contended that universal strategies for career advancement are inefficient. Their results endorse the application of division methods to pinpoint uniform clusters of educators who could gain from analogous training programs.

In recent times, examined mathematics educators' management of electronic gadgets in their learning environments. Employing a hybrid methodology, they uncovered multiple unique orchestration types, each marked by varying tool utilization, classroom conduct, and teaching tactics [10]. The writers emphasized the importance of differentiating among these types when designing training and help for math teachers..

1.2. Fuzzy C-Means Clustering in Educational Research

Despite such downfalls, hosting web-based system supports efficiency of the experiments and grants the use various types of machine learning algorithms for processing high complex data and highlighting concealed patterns that cannot be sensed through traditional methods [11]. Fuzzy C-Means (FCM) clustering may be a useful approach, in order to detect the patterns behind complex data sets. The FCM allows for geographically overlapping memberships with membership in multiple groups, conducive to analysis of complex teacher skills and practices. This was followed by an application of Fuzzy C-Means clustering to examine the learning behaviour in digital environments. Their results also demonstrated that FCM could successfully identify distinctive patterns of engagement and performance, and provide indications for customized interventions [12]. The authors underscored the benefit of fuzzy clustering over rigid clustering for educational data, where category borders are frequently indistinct.

In a recent investigation, examined data mining uses in education and recognized FCM as a promising method for analyzing educational data [13]. The writer observed that FCM's capacity to manage unpredictability and vagueness renders it especially apt for learning environments, where human actions and cognitive development are naturally intricate and multifaceted. Wang et.al [14] used a special method called FCM to look into what teachers need to learn and grow professionally. The research effectively found unique teacher categories based on their training needs, showing that FCM is useful for sorting teachers. The authors stated that the fuzzy method offered a deeper insight into teacher traits than standard grouping techniques.

1.3. Multicollinearity of Educational Data Analysis

Multicollinearity, particularly when examining the characteristics and practices of interconnected education, this is an important issue in educational data analysis. Several recent studies address this issue through a variety of methodological approaches. Kline [15] discussed the effects of multicollinearity on statistical analysis in educational research and recommended PCA as an effective strategy to reduce dimensions. The developers have emphasised that PCAs can retain its key information in their values and eliminate layoffs that lead to multicollinearity at the same time.

In examining data on the effects of teacher, Shen et al. [16] ound common collinearity between some educational practice variables. They applied PCA to produce the constitutive variables, which capture the latent dimensions of educational practice while retaining a lower-dimentional view of the data. Their approach demonstrated the effectiveness of PCA as a preprocessing step before the clustering algorithm was used.

Analyzed Howard and Thompson factors that influence teachers' adoption of digital tools, particularly in relation to technology integration [17]. They identified important multicollinearities between technology-related variables and PCAs used, and created interpretable components that represent various aspects of technology adoption. Your methodological approach provides a valuable precedent for addressing multicollinearity in the current study of cybergogy implementation data.

1.4. Mathematics Teachers and Digital Literacy

A number of recent researches focused on the relationship between teachers digital literacy and its implementation in Cybergogy. Instefjord & Munthe [18] studied the growth in their readiness to use digital tools by pre-service teacher and found significant variation in digital competence. The authors recommended, alternative approaches to teacher education based on the current digital literacy levels of teachers.

Considering mathematics specifically, Thurm [19] investigated the interplay of technological knowledge and pedagogical beliefs with classroom practices. This study saw digital literacy as a requisite state but not a sufficient one for technology integration of excellence in mathematics teaching. As the author stated that, digital literacy profoundly facilitated the relationship between teachers mathematics teaching and learning beliefs and classroom practice.

Complementing these results, Prodromou and Lavicza [20] examined teachers' use of digital tools in mathematics statistics teaching. They developed 3 technology infusion profiles for teachers within certain digital literacy levels and pedagogical knowledge/beliefs about mathematics. Resesarch supports this notion of need to differentiate in order to understand what driver technology implementation will be complex for certain teacher characteristics.

Semerci and Kemal [21] carried out an extensive investigation on mathematics teachers' digital literacy associated with their teaching routines by the way of a very comprehensive examination. Their research found significant associations among digital literacy levels and quantity of digital tools used in mathematical instruction. The authors advocated that professional development programs be directed to teachers' existing digital literacy level further supporting segmentation approaches.

2. Methods

This research employed a quantitative descriptive approach with a clustering analysis technique to segment the profiles of junior high school mathematics teachers based on their implementation of the Cybergogy model in classroom learning. The study's primary objective was to identify distinct clusters of teachers according to their knowledge, application, and technological integration of Cybergogy-based instructional practices, utilizing the Fuzzy C-Means (FCM) clustering algorithm. The research was conducted by independent study with primary data collection by the questionnaire survey of a random sample of both mathematics teachers in several junior high schools at Yogyakarta Special Region (DIY) and Central Java, Indonesia. It was then processed the collected data with Python and the data were also encoded and analyzed.

The sampling technique in this study was purposive sampling, in order to obtain samples that have relevant characteristics to the research purpose. Purposive sampling was used targeting teachers who were teaching and learning at the time of the data collection process [22] [23]. The population of this study were junior high school mathematics teachers in the Province of DIY. Data were obtained from members of the Mathematics Subject Teacher Working Group (MGMP) for junior high schools in DIY Province, selected based on specific criteria. This selection was based on the assumption that teachers who are members of the MGMP have active characteristics, a high enthusiasm for learning, and strong motivation to continue learning new things in the field of education. Additionally, these teachers frequently participate in training programs aimed at enhancing their professionalism as educators. Thus, the selection of this sample aims to obtain data from teachers who are more prepared and open to change and innovation in teaching, which is expected to provide deeper insights into the research topic. A total of 88 respondents participated in this study, representing various schools from urban and rural districts, ensuring a diverse data set in terms of teaching experience, digital literacy, and exposure to Cybergogy-based teaching strategies.

The clustering analysis was conducted based on several variables derived from the survey data [24]. These variables were grouped into four categories corresponding to the Cybergogy model's domains: Affective Engagement (A1: Years of Teaching, A2: Blended Learning Experience, A3–A8: Frequency of online learning implementation, knowledge and application of Cybergogy; Cognitive Engagement : K1–K4: Usage frequency and diversity of learning technologies; Emotional Engagement :E1–E4: Perceptions on student engagement and emotional connection during digital learning; Social Engagement : S1–S4: Collaboration practices and frequency of synchronous/asynchronous interaction methods)[25] Each variable was scaled and normalized to maintain uniformity across the dataset. The

Fuzzy C-Means (FCM) clustering method was chosen due to its ability to handle overlapping memberships, allowing each teacher to belong to multiple clusters with varying degrees of membership [26][27]. The FCM algorithm was implemented using the Scikit-Fuzzy (skfuzzy) library in Python [28].

To verify the independence of variables and prevent redundancy, a multicollinearity test was conducted using the Variance Inflation Factor (VIF) and correlation matrix analysis. Variables exhibiting VIF values exceeding 7.0, indicating strong collinearity, were candidates for removal or reduction [29]. To address this, Principal Component Analysis (PCA) was employed [30], using the sklearn.decomposition [31]. PCA module from Python's Scikit-Learn library. This dimensionality reduction technique transformed the original variables into a new set of uncorrelated components while preserving the majority of the data's variance [32].

This study was conducted in accordance with applicable ethical principles. Prior to data collection, this study obtained Ethical Clearance (ECA) from the authorized institution, as evidence that the research procedures have undergone an ethical evaluation process in accordance with academic and legal standards. Thus, all data used in this study were obtained with the full consent of the respondents and are protected in accordance with applicable data protection regulatioAll procedures performed in studies were in accordance with the ethical standards of the institutional research committee. Ethical Clearance (ECA) from the concerned institution for this study was secured as necessary evidence to support the fact that the research activities have been ethically reviewed based on academic and legal standards, before the data were collected. All data used in this study were collected with the full collaboration of the participants and are safeguarded according to the relevant data protection legal regulations.

3. Results and Discussion

This study aims to identify the segmentation of junior high school mathematics teacher profiles based on the implementation of the Cybergogy learning model. The Cybergogy model that integrates cognitive, affective, and social dimensions in technology-based learning requires strong pedagogical and technological readiness from teachers [25]. Therefore, the Fuzzy C-Means Clustering method was used to group teachers based on the pattern of Cybergogy implementation, supported by multicollinearity analysis and dimension reduction through Principal Component Analysis (PCA)

3.1. Multicollinearity Test

The results of correlation analysis revealed the existence of multicollinearity between the variables, particularly between the variables of technology use and Cybergogy implementation. This multicollinearity can lead to distortion in the cluster analysis [33] [34], which requires dimensionality reduction. Before clustering using Fuzzy C-Means algorithm, multicollinearity analysis was conducted on the variables in the dataset. The test results show that some pairs of variables have a fairly high correlation, characterized by a Pearson correlation coefficient value above 0.70, especially in variable groups related to the use of digital learning media (A1-A8) and the utilization of learning technology (K1-K4).

Multicollinearity analysis indicates that there is a high correlation value (>0.7) between several variables. Especially in the group of digital learning technology ability and efficacy variables, such as the correlation between the learning model application variable (A6) and learning technology knowledge (A5) of 0.70, the ability to manage virtual classes (K3) and digital learning evaluation ability (K4) of 0.71, and between interest in using ICT (S2) and views on the role of ICT (S3) of 0.79. This condition indicates the presence of multicollinearity that has the potential to destabilize the clustering model.

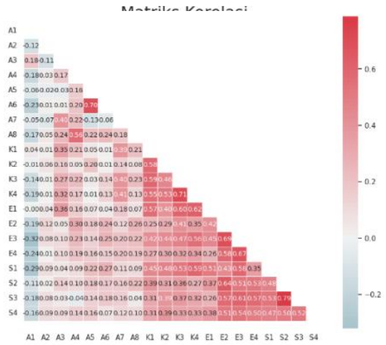

Figure 1. Correlation Matrixs

These values indicate the potential for strong multicollinearity among some variables, especially in the media utilization and e-learning skills indicator groups. If multicollinearity is not addressed, then clustering results can be biased because redundant information will dominate the cluster formation process. The correlation heatmap visualization shows that there are several groups of variables that have a close relationship with each other. For example, variable K1 (technology use) shows a strong correlation with K2, K3 and K4, which represent similar dimensions of technology application. Likewise, E1 and E2, which relate to the experience of using digital media, have high correlations with each other. These correlations demonstrate that some variables are redundant and the clustering patterns can be biased due to the redundancy. Accordingly, the dimensionality reduction by PCA was conducted to reduce the possible multicollinearity and enhance the clustering model. Multiple regression is then conducted through the principal component analysis (PCA) dimension-reduction approach to alleviate multicollinearity. By doing PCA we get first two main components that explain over 60% of the variance, so the data is becoming more homogeneous and ready for analysis.

3.2. Principal Component Analysis (PCA)

PCA (Principal Component Analysis) is a statistical approach to reduce the data dimensionality while retaining the maximum information [35]. In this study, PCA was used to avoid multicollinearity in the instrumental variables (in this research) [36]. PCA analysis indicates that two of the principal components are able to account for a substantial level of data variance, PC1 and PC2.

PC1 has an eigenvalue of 4.2 and explains 40% of the total variance with the greatest factor loadings such as E2 (Efficacy of Managing Online Learning), K1 (Ability to Design Digital Learning), and S2 (Interest in Using ICT). This is consistent with observations by Jolliffe & Cadima [37], that the first PCA component tends to explain the majority of the variance in presence of highly correlated variables. PC2, with an eigenvalue of 2.3, explained about 20% additional variance. Variables that contribute significantly to PC2 include A6 (Learning Model Implementation) and A7 (Internet Utilization). This component indicates a practical implementation dimension of technology use in learning, distinct from competence or self-efficacy reflected in PC1.

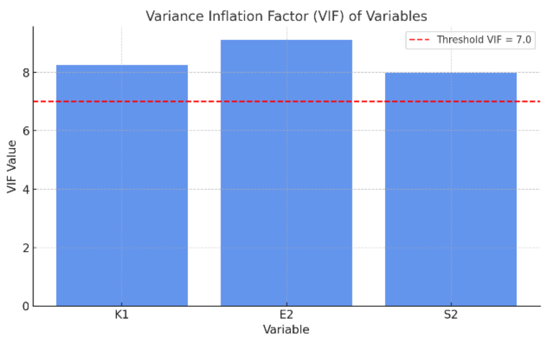

Figure 2. Variance Inflation Factor (VIF)

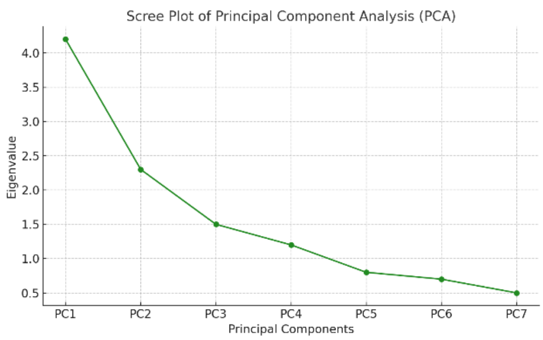

Figure 3. Scree Plot of PCA

Visualization of the PCA results through the scree plot shows a sharp "elbow" after the second component, indicating that two principal components are sufficient to describe the basic structure of the data [38]. Therefore, the data is then projected to this two-dimensional space to facilitate the clustering process using Fuzzy C-Means. Data transformation using PCA not only improves computational efficiency, but also clarifies the cluster structure in the data. As stated by Shlens (2014), dimension reduction with PCA allows the separation between clusters to become more apparent, especially when the initial data has many redundant attributes.

PCA successfully reduces variables into fewer components while retaining essential information, thus improving clustering quality. The use of PCA in fuzzy clustering is also supported by literature showing that PCA can improve the interpretability and accuracy of segmentation in data-driven educational research [37]With this approach, the clustering process becomes more effective, because the data used is free from the influence of multicollinearity and only includes the main dimensions relevant to the teacher profile in the implementation of Cybergogy.

3.3. *Implications of Multicollinearity Analysis and PCA on Fuzzy C-Means Clustering*

The FCM clustering results showed convergence at the 6th iteration with an objective function value of 620.006, indicating the stability and reliability of the segmentation. Two main clusters were formed, with relatively close final centroids but reflecting differences in teacher characteristics in terms of the application of the Cybergogy model. The objective function at iterations 1 to 6 showed a significant and stable decrease in value, indicating a convergent FCM clustering process.

Table 1. Objective Function Beginning to end

Iterations	Objective Function Value
1	780,664
2	620,245
3	620,024
4	620,009
5	620,007
6	620,006

The cluster centroid for variables such as length of teaching (A1), blended learning experience (A2), frequency of blended learning (A3), knowledge of learning technology (A5), application of learning models (A6), and aspects of digital ability and efficacy (variables K1-K4, E1-E4, S1-S4) provide an overview of the profile of each group of teachers. Most of the cluster centroid values range from 2.0 to 4.0, indicating a medium to good level of teacher application and confidence in the use of learning technology. Differences in centroid values for certain variables, such as K3 (ability to manage virtual classes) and E2 (efficacy in managing online learning), although small, indicate variations in teachers' abilities and experiences in implementing the Cybergogy model. The degree of fuzzy membership shows that most teachers have a balanced level of membership between the two clusters, which reflects the characteristics of teachers who are not entirely homogeneous and have varying levels of technological adaptation. This is consistent with the phenomenon commonly encountered in the adoption of learning technology in diverse educational environments.

3.4. *Cluster Validity*

Cluster validity is measured using the *Partition Coefficient Index* (PCI), which is one of the popular methods in fuzzy clustering to assess the degree of segmentation clarity. PCI measures the consistency and certainty of data membership to the formed clusters. PCI values range from 0 to 1, with higher values indicating clearer and unambiguous clusters. Cluster validity is an important aspect in fuzzy clustering that has been widely discussed in recent literature. Huang et al. [39]stated that evaluating cluster validity with an index such as PCI is crucial to ensure that the segmentation reflects the true differences in characteristics within the teacher population. In addition, Sinclair [10]emphasized that good cluster validity will increase the effectiveness of developing learning strategies based on segmentation. Based on the results of the PCI calculation in this study, the cluster validity value is obtained in table 2.

Table 2. Cluster validity

Number of Clusters	PCI Value
2	0,5578
3	0,3845
4	0,2790

The highest PCI value of 0.5578 was obtained for segmentation with two clusters, indicating that two clusters is the most optimal and valid number of clusters for junior high school math teacher data in this study. Lower PCI values at cluster numbers 3 and 4 indicate increased ambiguity and decreased clarity of segmentation. A PCI value of 0.5578 indicates moderate to good segmentation clarity. In the context of education and psychometrics, PCI values above 0.5 are considered adequate for segmentation that can be used as a basis for decision-making, especially regarding the development of training or interventions focused on the characteristics of each teacher cluster.

The relatively balanced fuzzy membership between clusters in most of the data indicates that there are teachers who have cross-cluster characteristics, which is in accordance with the concept of fuzzy clustering that accommodates ambiguity and variation in individual profiles. Furthermore, Jolliffe & Cadima [37]asserted that the validity of clusters generated from data that has been reduced in dimension by PCA (as in this study) will be more stable and reliable, because it reduces noise and redundancy of variables that can obscure segmentation. This strengthens the interpretation that the resulting clusters are not only statistically valid, but also meaningfully reflect the complex and overlapping traits of real-world teacher profiles.

Based on data processing, FCM clustering produces two main clusters that represent two different segments of junior high school math teachers in the application of the Cybergogy model. The clustering iteration process shows convergence at the 6th iteration with an objective function of 620.006, which indicates the stability of the clustering model and the reliability of the segmentation results. The initial and new fuzzy membership degrees show that most teachers have a relatively balanced membership distribution between two clusters, in accordance with the characteristics of fuzzy clustering that accommodates data ambiguity and allows objects to have membership in several clusters at once. The cluster centroid is a representation of the average variable in each cluster that describes the profile of teacher characteristics in each segment.

In general, the two clusters have relatively similar profiles with small but significant differences in centroid values on some technology and digital efficacy variables. Cluster 2 shows a trend towards slightly higher scores, indicating teachers with better levels of application and confidence in using the Cybergogy model. Variables E2 and E4 (efficacy in managing online learning and designing digital content) have the highest scores, indicating that teachers in both clusters generally feel quite confident in the aspect of managing digital learning.

The clustering results show that junior high school teachers in Yogyakarta can be grouped into two main categories in terms of their understanding and implementation of the Cybergogy learning model. Cluster 1: Proactive Cybergogy Adopters - Teachers with a high understanding of Cybergogy and consistent use of technology. Cluster 2: Emerging Cybergogy Learners - Teachers with sporadic technology adoption and limited understanding of Cybergogy.

Table 3. Cluster Centroid

Variables	**Cluster 1 (C1)**	**Cluster 2 (C2)**
Years of Teaching (A1)	3,1130	3,0916
Blended Learning Experience (A2)	0,9768	0,9778
Blended Learning Frequency (A3)	2,8213	2,8378
Virtual Platform Used (A4)	2,7054	2,7264
Knowledge Technology (A5)	1,9178	1,9231
Application of Learning Model (A6)	2,0387	2,0522
Internet Utilization (A7)	1,7079	1,7239
Type of Technology Used (A8)	2,2650	2,2804
Ability to Design Digital Learning (K1)	3,5655	3,5936
Ability to Use LMS (K2)	3,3166	3,3425
Ability to Manage Virtual Classroom (K3)	3,0380	3,0757
Digital Evaluation Capability (K4)	3,0272	3,0637
Confident in Using Technology (E1)	3,2251	3,2521
Efficacy of Managing Online Learning (E2)	4,1217	4,1510
Confidence in Overcoming Technology Problems (E3)	3,9266	3,9598
Efficacy in Designing Digital Content (E4)	4,0436	4,0700
Positive Attitude towards Technology (S1)	3,4293	3,4571
Interest in Using ICT (S2)	4,0671	4,0919
Views on the Role of ICT (S3)	3,9295	3,9568
Comfort using technology (S4)	3,5098	3,5356

Cluster 1 tends to have higher scores on indicators of digital media usage skills (A1-A8) and attitudinal aspects (S1-S4). This is in line with findings stating that the adoption of technology-based learning models is strongly influenced by digital literacy and teaching experience [35,40]. Meanwhile, Cluster 2 is more dominated by teachers who have relatively limited e-learning experience before the pandemic, as well as a low understanding of the concept of Cybergogy. This phenomenon suggests that although the pandemic has encouraged massive implementation of online learning, the transfer of Cybergogy-based pedagogical competencies still needs to be improved through continuous training. This result is also in line with the theory proposed by Francisco [41]which states that in the implementation of Cybergogy-based learning, motivational factors, technological skills, and teaching experience have a significant contribution in shaping the success of the online learning process.

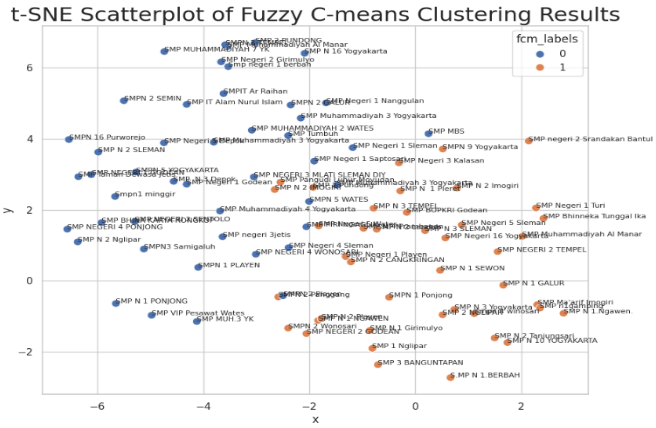

Figure 4. t-SNE Scatterplot FCM Clusterring

3.5. Interpretation of Cluster Profiles and Characteristics

According to Huang et al. (2024) [42], a sustainable digital pedagogy approach provides the foundation for modern education systems to implement advanced digital technologies in sustainable educational transformation. Thus, data-driven teacher segmentation (clustering) can improve the effectiveness of data-driven decision-making in education. By grouping teachers according to their digital expertise or readiness profiles, professional development policies and learning strategies can be tailored more effectively. Informative segmentation results also support sustainable digital transformation; for example, the implementation of innovative professional learning community models that emphasize the use of digital technology and effective teaching strategies has been shown to drive sustainable pedagogical paradigm shifts [43]**.** Furthermore, the resulting cluster profiles are contextual and dynamic, making them a solid foundation for measurable educational interventions. Kalliomäki-Levanto et al. [44], demonstrate that analyzing teachers' digital activity clusters yields “action-oriented” and contextual information, which is useful for identifying intervention targets. As a result, policymakers and school leaders can design more targeted interventions and training tailored to the characteristics of each cluster, supporting the sustainable improvement of digital learning practices [43].

Teachers in Cluster 1 show high readiness for technology-based learning, in line with the results of research by Francisco [41]. While Cluster 2 requires additional training interventions, as stated by Hatlevik et al. [45]in their study on teachers' digital competencies. The infographic emphasizes the competency gap between clusters. Teachers in Cluster 1 show high scores in all dimensions, while Cluster 2 requires strengthening in digital literacy and Cybergogy-based pedagogy. Comparison of cluster profiles emphasizes the significant difference between Proactive Cybergogy Adopters and Emerging Cybergogy Learners. In the aspects of understanding Cybergogy, using technology, integrating Cybergogy principles, digital readiness, and potential to train peers, teachers in Cluster 1 consistently show the highest scores, close to the maximum value. In contrast, teachers in Cluster 2 displayed lower scores on all these aspects. This visualization supports the importance of a differentiated approach in real needs-based teacher training [40]. This visualization clearly illustrates that teachers in Cluster 1 are not only able to adopt technology in learning, but have also internalized the pedagogical principles of Cybergogy into their professional practice [41].

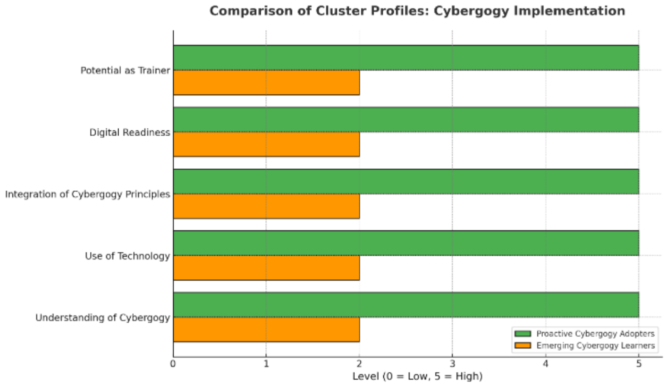

Figure 5. Comparison of Cluster Profile

Meanwhile, teachers in Cluster 2 still need strengthening in many dimensions to be able to implement technology-based learning optimally [45]. Thus, this infographic clarifies the urgency of developing a teacher capacity development strategy based on the segmentation of real needs. Table 4 shows the fundamental difference between the two clusters of teachers in this study. Teachers in Cluster 1 show high readiness in adopting and implementing Cybergogy learning model with strong technology literacy support. They actively integrate the main principles of Cybergogy in their teaching practice. In contrast, teachers in Cluster 2 are still in the early stages of adoption, with sporadic use of technology and limited understanding of Cybergogy principles, thus requiring further intervention in the form of training and digital competency development.

Table 4. Cluster Characteristics

Aspects	Cluster 1 (C1)	Cluster 2 (C2)
Understanding Cybergogy	High	Limited
Use of Technology	Consistent, Multiple Platforms	Sporadic, Limited
Integration of Cybergogy Principles	Active (Collaboration, Independence, Socialization)	Lack of Integration
Digital Readiness	Very Ready	Needs Improvement
Potential to Train Others	High	Low

3.6. Teacher Segmentation for Data-Driven Decision for Enhancing Sustainable Digital Pedagogy

Segmenting teachers based on their technological readiness or pedagogical profile provides more in-depth data to support evidence-based decision-making in education systems. Through this approach, education leaders can design more targeted training programs and allocate resources effectively to drive sustainable digital transformation. Segmentation also helps identify groups of teachers who need basic or advanced digital competency improvement according to field needs [46]. Training strategies tailored to the digital maturity level of each cluster will increase learning effectiveness and strengthen teacher professionalism [47].

Clustering results also facilitate the formulation of measurable education policies that are aligned with the direction of digitalization. Each teacher group can serve as the basis for setting specific digital competency achievement indicators, so that policy implementation can be monitored based on target achievement [45]. By utilizing cluster analysis, training can be personalized—teachers in clusters with low competencies receive intensive training, while clusters with high competencies act as mentors or advanced technology developers (Bianca Ifeoma Chigbu, 2017; Karime, 2025). This data-driven approach helps policymakers design adaptive and sustainable interventions, supporting long-term digital transformation in education [9].

Based on the results of the segmentation of junior high school mathematics teachers in implementing the Cybergogy model, a series of strategic recommendations are needed to strengthen teachers' professional development, accelerate the adoption of technology in learning, and improve the quality of digital learning in general. These recommendations are designed by considering the characteristics of each cluster. The recommendations for Cluster 1- Proactive Cybergogy Adopters are Empowerment as

Change Agents [48], Involvement in Digital Curriculum Development [49], Advanced Capacity [50], Rewards and [51]. Recommendation for Cluster 2: Emerging Cybergogy Learners are Basic Digital Literacy and Cybergogy Pedagogy Training Intensive coaching and mentoring programs [40], Improved Access to Technology and Infrastructure [48], Empowerment in Communities of Practice [45].

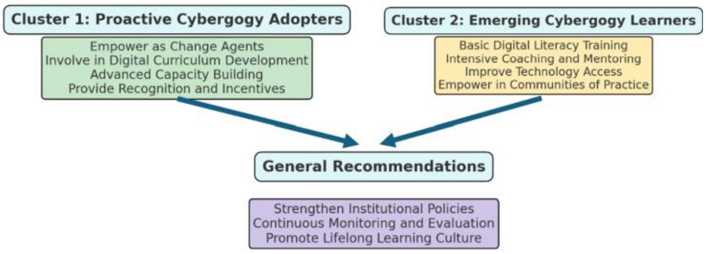

Figure 6. Strategic Recommendation Based on Clustering Analysis

4. **Conclusion**

The research successfully identified two main segments of junior high school mathematics teachers based on the profile of the application of the Cybergogy model with the Fuzzy C-Means method. Dimensional reduction with PCA overcomes multicollinearity between variables, improving clustering quality. The centroid profile shows differences in teacher characteristics related to ability and efficacy in using digital learning technology. The t-SNE visualization strengthens the segmentation results by showing a clear yet flexible cluster distribution according to the concept of fuzzy clustering. Good cluster validity supports the use of segmentation results as a basis for developing more effective and personalized training strategies. The analysis results show significant differences in the level of understanding and application of the Cybergogy model between the two segments, with Cluster 1 showing higher digital readiness than Cluster 2. Dimensionality reduction using PCA successfully overcame the problem of multicollinearity between variables, improving the quality of the clustering results.

These findings contribute significantly to efforts in the digital transformation of education, particularly in supporting teacher professional development. Strategic recommendations based on the segmentation results can accelerate technology adoption in learning and improve the quality of digital learning. For Cluster 1, which has already demonstrated good technology adoption, an empowerment approach as agents of change and further capacity building are essential. Meanwhile, for Cluster 2, which requires more support, basic digital literacy training programs and intensive mentoring are crucial to accelerate mastery of Cybergogy principles.

From a policy perspective, the research findings provide recommendations for stakeholders and policymakers to design more targeted and needs-based training policies, taking into account the characteristics of each teacher group. This will support the sustainability of educational technology and create an inclusive innovation ecosystem in schools. Enhancing teachers' capacity through training tailored to these segments is expected to accelerate digital transformation in education and improve the quality of education at the system level in a measurable way.

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