

Research Article

Implementation of the K-Means Method for Segmentation of Student Data Based on Learning Style: A Case Study in the Informatics Study Program

Gunawan Prayitno

Sekolah Tinggi Manajemen Informatika Dan Komputer Pesat Nabire (STMIK Pesat Nabire), Jl. Poros Samabusa, Sanoba, Distrik Nabire, Kabupaten Nabire, Papua 98816, email: binaanakpapua@gmail.com

* Corresponding Author: binaanakpapua@gmail.com

Abstract: Adapting to students' learning styles is a key factor in enhancing the effectiveness of higher education, particularly in Informatics programs where learning preferences vary widely. This study aims to segment students based on their learning styles using the K-Means clustering algorithm, guided by the VARK model (Visual, Auditory, Read/Write, Kinesthetic). Data were collected from 130 Informatics students, including information on their learning preferences, and processed through normalization techniques. The optimal number of clusters was determined using the Elbow Method and Silhouette Score, and subsequent cluster interpretation was conducted. The results identified three dominant clusters, each representing distinct learning behavior patterns. These clusters were analyzed to recommend tailored instructional strategies for each group. Specifically, Visual learners were found to benefit from graphic-heavy materials, Auditory learners preferred lectures and discussions, Read/Write learners thrived on written content and detailed notes, while Kinesthetic learners responded best to hands-on activities. The findings support the development of adaptive, data-driven teaching approaches that align with the actual learning tendencies of students in Informatics. Moreover, the study demonstrates that the K-Means method is effective in systematically identifying student learning profiles, which can be used to inform instructional improvements. This personalized approach to teaching could significantly enhance learning outcomes by providing students with the most effective educational experiences tailored to their individual learning styles.

Keywords: Informatics education; K-Means clustering; Learning styles; VARK model; Visual learners

1. Introduction

Understanding students' learning styles plays a very important role in increasing learning effectiveness, especially in the field of Informatics which requires students to master theoretical concepts as well as practical skills. Each student has a different learning style that can be categorized based on the VARK model (Visual, Auditory, Reading/Writing, and Kinesthetic). Research by Jahring shows that identifying learning styles can help educators plan and tailor more effective teaching methods for each student, taking into account their learning modalities (Jahring, 2019) Thus, this learning approach that pays attention to learning

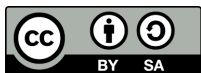
Received: August 16, 2025

Revised: August 30, 2025

Accepted: September 14, 2025

Published: September 16, 2025

Curr. Ver.: September 16, 2025



Copyright: © 2025 by the authors.

Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY SA) license

(<https://creativecommons.org/licenses/by-sa/4.0/>)

styles can help students in achieving a better understanding of the material being taught (Habibah et al., 2019).

2. Preliminaries or Related Work or Literature Review

However, in practice, many lecturers still apply uniform teaching methods without considering the differences between students' learning styles. This can result in dissatisfaction and low learning effectiveness. Kurniawan and Riswanto point out that if the education system is based on a uniform approach, then this has the potential to reduce learning outcomes due to a lack of attention to the uniqueness of each student (Kurniawan & Riswanto, 2023) In addition, the results of research by Irawati revealed that there is a significant influence of learning style on student learning outcomes, where those who are taught by paying attention to their learning style tend to get better results (Irawati et al., 2021)

On the other hand, technological developments, especially in e-learning-based learning, provide opportunities to overcome this problem. Research by Nugraha and Budiyo introduced an adaptive e-learning system based on VARK's learning style, which allows for a more personalized delivery of material to students (Nugraha & Budiyo, 2022) Research by Hasanun et al. shows that with the adjustment of e-learning to students' learning styles, their understanding of the material can improve (Hasanun et al., 2023) This conclusion shows that innovation in learning methods, especially those that utilize technology, is very important to be integrated in education in the field of Informatics to maximize student absorption.

Penelitian mengenai penerapan metode K-Means clustering dalam mengelompokkan mahasiswa berdasarkan gaya belajar VARK memiliki potensi yang signifikan untuk meningkatkan efektivitas pengajaran. Dengan memanfaatkan teknik data mining ini, peneliti berharap dapat menciptakan segmentasi yang lebih tepat dan sesuai dengan karakteristik kognitif mahasiswa. Kholidin et al. menunjukkan bahwa algoritma K-Means mampu memberikan segmentasi yang valid dalam konteks gaya hidup mahasiswa, di mana hasil analisis cluster dapat digunakan untuk merancang program intervensi kesehatan yang lebih sesuai bagi masing-masing kelompok mahasiswa (Kholidin et al., 2024). Oleh karena itu, penerapan metode ini dalam konteks gaya belajar diharapkan dapat membantu pengajar merancang strategi belajar yang lebih adaptif.

On the other hand, in data limited conditions, the use of K-Means clustering can result in good classification performance. Research by Nabilla et al. shows that despite the challenges in image segmentation using K-Means, this method is still reliable to generate useful information in the context of classification (Nabilla et al., 2022) This is relevant for learning style grouping, where data obtained from surveys or student learning style measurements can be processed to identify patterns that emerge among individuals. In addition, the potential for K-Means to be used in academic contexts depends on proper data processing and an understanding of students' learning patterns that can help achieve optimal learning outcomes (Akbari & Kerlooza, 2018)

The findings of various studies support the application of the K-Means clustering method in the context of education. Rachmatika and Bisri show that the use of the K-Means algorithm can provide a deeper understanding of student behavior as a basis for improving the education system (Rachmatika & Bisri, 2020) Taking these results into account, a data-

driven approach that integrates the characteristics of students' learning styles through K-Means can be used as a foundation for developing more responsive curriculum and teaching modules. This approach is expected not only to facilitate better learning but also prepare students to face challenges in an increasingly complex era of education.

The VARK learning style model, introduced by Neil Fleming, groups individual learning into four categories: Visual, Auditory, Reading/Writing, and Kinesthetic. This model aims to provide a better understanding of individual learning preferences, and has been widely applied in educational contexts to tailor teaching methods to the needs of students. Research shows that when teaching is tailored to students' learning styles, there is an increase in motivation and learning effectiveness, especially in courses that require a deep conceptual understanding, such as programming and information systems (Amaniyani et al., 2020) (Hernandez et al., 2020). In particular, the VARK model can assist teachers in designing a more inclusive curriculum to meet students' diverse learning styles (Aishah Noor & Amri Ramly, 2023)

Several studies have shown that learning style mapping through the VARK model can affect learning outcomes. For example, teaching implemented through concept maps has been shown to be more effective than traditional lecture methods, especially for students with visual learning styles (Amaniyani et al., 2020) In addition, research shows that students who identify as kinesthetic learners respond better to more interactive and experiential learning methods (Hernandez et al., 2020) With an emphasis on more diverse teaching methods, studies indicate that the implementation of the VARK model can help create a more engaging and effective learning experience for students (Kanojiya, 2023)

While there is evidence to support the benefits of the VARK model, its implementation is often not data-driven. Many teachers still use a uniform approach in teaching, without taking into account the data of students' learning styles systematically (Ismail & Azlan Haniff, 2020) (Khamphaya et al., 2022) This reflects the need for an evidence-based approach in the development of classroom teaching strategies. Recent research underscores the importance of more accurate data collection on students' learning styles, which can support the use of innovative teaching strategies that are more tailored to the needs of learners in academic settings (Maidin et al., 2023) (Chandrasekera et al., 2024) (Michalowski et al., 2021). The application of this data-driven research will not only increase teaching effectiveness but can also improve overall student learning outcomes.

The K-Means clustering algorithm has become an invaluable tool in educational data clustering with the ability to identify hidden patterns in data without supervision. This technique is widely applied to group students based on learning behavior, academic outcomes, and other demographic characteristics. Previous research has shown that K-Means-based grouping makes it possible to analyze and understand segments in the student population, thus creating a more strategic approach in teaching and curriculum planning Agha et al. (Agha et al., 2023). Through the analysis of educational data, K-Means helps educators identify the specific needs of student groups, which can positively impact more focused and adaptive educational interventions (Dinata et al., 2020)

Combining the VARK model with the K-Means algorithm can generate clusters of students based on objective learning preferences, allowing for the development of more appropriate learning strategies. By leveraging segment data generated from K-Means, teachers

can tailor their teaching methods to meet the learning needs of each student, including paying attention to variations in learning styles (Aishah Noor & Amri Ramly, 2023) The results of the study showing that the combination of K-Means and VARK provide positive results in increasing student engagement and understanding, confirms the importance of a data-driven approach in learning (Ismail & Azlan Haniff, 2020) By adopting these techniques, educational institutions can achieve the goal of building an inclusive learning environment that is responsive to individual needs.

Although the use of K-Means in the context of education is becoming more popular, there are still limited studies that specifically apply it to students of the Informatics study program. Research focusing on the development of learning style data-based learning strategies in the Informatics study program shows that this method can improve learning outcomes and student engagement, especially in materials that demand more attention (Kanojiya, 2023) The findings show that the K-Means algorithm can be used with high efficiency even under limited data conditions. This is expected to serve as a basis for further research exploring the potential of other algorithms in the same context and provide inspiration for the development of more targeted learning models in the field of Informatics (Newton & Salvi, 2020)

3. Proposed Method

This study utilizes a descriptive quantitative approach with the aim of classifying students based on their learning styles identified through the VARK model. Students who are active in the Informatics Study Program at one of the private universities are the subjects of this study, with a total of 120 respondents selected through purposive sampling techniques. This method allows researchers to focus on individuals who have certain characteristics, in this case students who are active in the study. Data collection was carried out by distributing the VARK questionnaire online through Google Form, which indicates the ease of data collection and accessibility for students. In addition, the transformation of questionnaire answers into numerical data is an important step to streamline the analysis process (Mohajan, 2020)

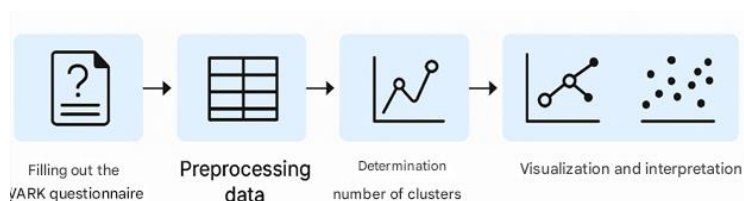


Figure 1. Complete Flow of Learning Style Segmentation Process Using K-Means.

This infographic describes the main stages of segmentation of student learning styles, starting from filling out the VARK questionnaire, preprocessing data, determining the number of clusters, to the process of visualizing and interpreting clustering results using the K-Means algorithm.

In this study, the validity of the instrument's content was tested through expert analysis, ensuring that the questionnaire used was relevant and appropriate to measure learning styles according to the VARK model. Internal reliability is estimated using internal consistency testing, which is a commonly used method to ensure that measurement

instruments produce consistent and reliable results (Mayasari et al., 2021) Previous research has also shown that an understanding of individual learning styles can improve academic success, although the relationship between specific learning styles and academic outcomes is not necessarily significant for all groups of students. This is in line with the argument that despite variations in learning preferences, relevant teaching strategies are still important for improving overall learning outcomes.

The findings of this study show that by using VARK as a tool to identify learning styles, valuable information about students' learning preferences is obtained. Data obtained through the VARK questionnaire showed significant variation in learning styles among students, allowing teachers to adapt their teaching methods to be more effective. As explained by Ilahana and Rachmawati, the descriptive quantitative approach aims to provide an in-depth picture of the existing situation, which in this context is the learning style of students (Ilahana & Rachmawati, 2022) Thus, the results of the study not only provide information about students' learning styles, but also have the potential to guide the development of teaching methods that are more responsive and in accordance with the needs of students (Bhayangkara et al., 2019).

The data that has been collected in this study was analyzed using the K-Means clustering algorithm to identify student groups based on the similarities in learning styles identified through the VARK model. The analysis process begins with an important data preprocessing stage, where inconsistent or missing data is addressed to improve the quality of the analysis. In this context, effective preprocessing techniques guarantee that the dataset is ready for analysis, helping to improve the classification obtained through the K-Means method. Once the data is prepared, the optimal number of clusters is determined using the elbow method, which is a visualization technique that helps in identifying the points where the addition of new clusters does not provide a significant increase in data variation (Shahapure & Nicholas, 2020)



Figure 2. Stages of Data Analysis Using the K-Means Method.

This figure explains the five main stages in the analysis of research data, starting from the collection of VARK data to the visualization of cluster results.

Furthermore, the evaluation of clustering results was carried out using silhouette score, which is a metric that provides an idea of how well a cluster member is separated from other clusters (Shutaywi & Kachouie, 2021) A high silhouette score indicates that the classified sample is in the appropriate cluster, while a score close to zero or negative indicates that the data could have been fed into another cluster. In this study, the use of Python and the scikit-learn library provides ease in the implementation of the K-Means algorithm, as well as helps in the visualization of cluster results in the form of two-dimensional graphs, thus facilitating further analysis and interpretation by researchers and teachers (Gede Sarasvananda et al., 2019). The use of this visualization also supports the depiction of the characteristics of

each of the resulting clusters, which is important in the context of adaptive learning strategy recommendations.



Figure 3. Complete Flow of Learning Style Segmentation Process Using K-Means.

This figure shows five main stages in the data analysis process in the research, namely filling out the VARK questionnaire, preprocessing data, determining the number of clusters using the elbow method, applying the K-Means clustering algorithm, and the final visualization of the results of student learning style segmentation.

The clustering results obtained with this approach can provide important insights into the characteristics of students based on their learning style. By identifying and grouping students into clusters based on learning styles, researchers can recommend learning strategies that are more appropriate to the specific needs of each group (“Leveraging TF-IDF Matrix for Document Clustering With K-Means Algorithm,” 2024) These findings show consistency with previous research that emphasizes the importance of adjusting teaching methods based on students' learning styles to improve educational effectiveness (Hao et al., 2021) Therefore, the results of this study not only contribute to academic understanding, but also provide practical guidance for the development of more responsive and individualized teaching strategies, along with improving overall student learning outcomes.

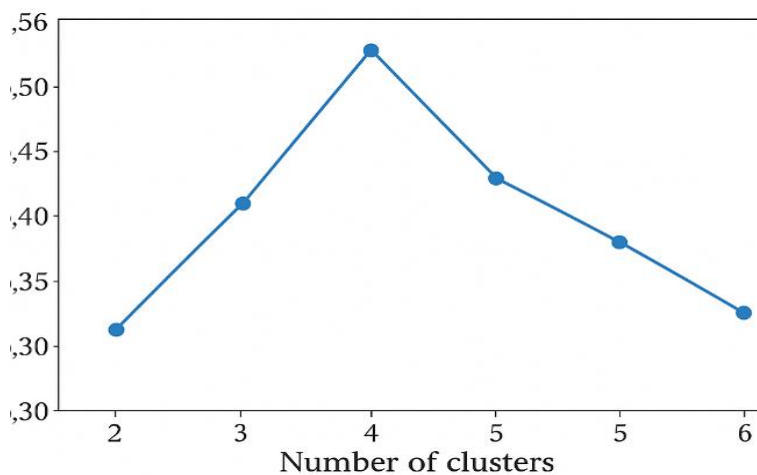


Figure 4. Silhouette Score Evaluation for Cluster Validity.

This chart illustrates the silhouette score values for cluster counts ranging from 2 to 6. The peak score at $k = 3$ supports the decision to use three clusters in the K-Means segmentation of student learning styles.

4. Result

Of the total 120 respondents who participated in this study, the results of the VARK questionnaire revealed a diversity of learning styles among students with a dominant tendency towards kinesthetic and visual types. Research on learning styles using VARK instruments is a proven and validated approach, focusing on four sensory modalities, namely visual, auditory,

read/write, and kinesthetic (Karim et al., 2023) These results are in line with studies showing that students often show preferences that reinforce this tendency, where kinesthetic learning styles are often associated with more active and participatory learning processes (Karim et al., 2019).

The data normalization process carried out in this study shows that the analysis using the elbow method proves that the optimal number of clusters is three. K-Means clustering was then applied to group respondents based on identified learning style patterns. These results are analyzed in line with previous research that has used K-Means clustering to analyze students' learning styles and highlight the importance of clustering in learning that can improve the educational experience (Beldar et al., 2023) (Gede Sarasvananda et al., 2019) The first cluster is dominated by students with visual learning preferences, the second cluster includes auditory and reading/writing learning styles, and the third cluster shows the dominance of kinesthetic types, confirming that different educational approaches are needed to meet the needs of each group.

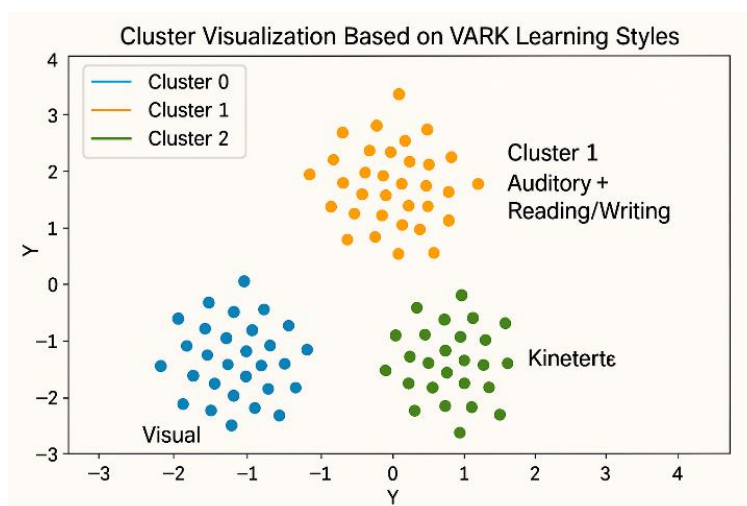


Figure 5. Visualization of Clustering Results Based on VARK Learning Style.

This graph shows three learning style clusters formed from the K-Means algorithm: Cluster 0 (Visual) is blue, Cluster 1 (Auditory + Reading/Writing) is orange, and Cluster 2 (Kinesthetic) is green. Each point represents a student who is grouped based on the similarity of learning preference patterns.

Validation of the clustering results was carried out using a silhouette score, which resulted in a value of 0.56. This value shows a fairly good and stable level of cluster separation, which is in line with evaluations conducted in other studies where silhouette scores were used to assess cohesion and separation between clusters. This good level of separation is important because it reflects the effectiveness of grouping learning styles that can support teaching strategies that better suit students' learning preferences, thus enabling them to achieve higher academic potential.

Visualization of clustering results with two-dimensional graphs is an effective tool in showing the distribution and characteristics of each cluster that illustrates the diversity of student learning styles. Through this visualization, clusters can be clearly shown, emphasizing the striking differences between visual, auditory, and kinesthetic learning styles. According to Irmanda et al., students' learning styles are very important to know in order to facilitate the learning process (Irmanda et al., 2020) The clear separation between clusters in the graph

shows that students with kinesthetic learning styles are more likely to respond to the practicum approach, while students with visual learning styles prefer graphical representations such as schematics and diagrams (Irennada et al., 2022).

The success in developing differentiated learning strategies can be supported by the results of the clustering. Fitri and Solihati noted that the application of differentiated learning allows for teaching that is more in line with the characteristics of students (Fitri & Solihati, 2023). In this context, the strategies designed can be more directed, especially in accommodating the uniqueness of different learning styles among students. For example, the practicum approach is effective for students with kinesthetic learning styles, while visual students can be better reached through graphic media and visual-based presentations (Herwina, 2021).

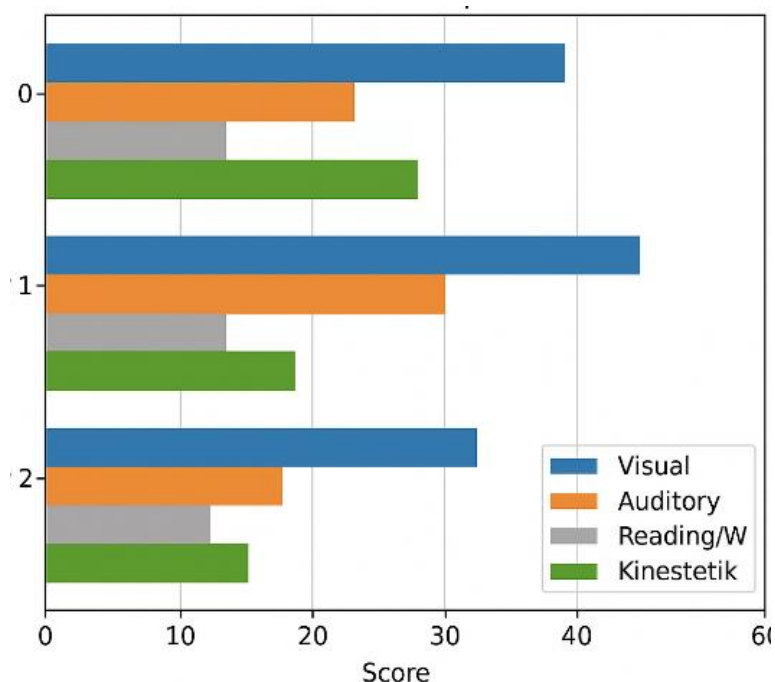


Figure 6. Distribution of VARK Scores per Cluster.

This bar chart illustrates the average scores of four VARK learning style dimensions—Visual, Auditory, Reading/Writing, and Kinesthetic—for each cluster generated by the K-Means algorithm. The distribution highlights the dominant learning style tendencies within each cluster, providing a quantitative foundation for the development of adaptive and targeted teaching strategies.

Furthermore, the results of the study show that the segmentation of learning styles carried out through data mining not only improves the personalization of the learning experience, but also paves the way for the development of relevant and effective teaching modules (Delima & Budianingsih, 2020) Through this approach, teachers are expected to reach a wide range of student characteristics, which in turn can improve students' academic ability and learning interest (Hilman et al., 2023) Thus, the visualization of clustering results clearly provides valuable guidance in developing a more holistic and responsive educational approach to the needs of students in the field of Informatics.

Summary of Learning Style Characteristics in Each Cluster

Dominant Style	Preferred Method	Teaching Implication	Example Media	
Visual	Diagrams, Charts	Use visual aids	Infographics Slides	34%
Auditory+ Read/Write	Discussions Notes	Combine verbal +	Podcasts Handouts	31%
Kinesthetic	Hands-on Practice	Interactive learning	Labs Simulations	35%

Figure 7. Summary of Learning Style Characteristics in Each Cluster.

This table summarizes the dominant learning style, preferred learning method, instructional implication, suggested media, and cluster composition percentage for each student group identified through K-Means clustering.

5. Discussion

The results of segmentation carried out on the learning style of Informatics students showed that their learning patterns were not homogeneous. The study used the K-Means algorithm to group the data, which successfully identified three different clusters. These findings are in line with the VARK model proposed by Fleming, in which there are unique aspects of individual learning preferences, such as visual, auditory, literary, and kinesthetic. In the context of Informatics students, this variety of learning styles is very important to understand, considering that this discipline involves many technical and logical aspects that can be understood differently by each individual. By understanding that there is no truly universal approach to learning in an academic environment, we can begin to adapt teaching materials to better meet each student's learning needs and preferences. The silhouette score obtained from cluster analysis was 0.56, which indicates that the formed cluster is quite solid and reliable for further analysis. These values indicate that individuals in the same cluster have a higher similarity in learning styles compared to individuals in different clusters.

The use of silhouette score as a powerful metric in cluster model validation supports the reliability of the results obtained from the K-Means algorithm applied. This proves that this analysis not only provides an idea of the separation between students' learning styles, but also justifies the use of data in making better decisions regarding appropriate teaching methods. The three clusters identified not only showed variations in learning styles, but also had significant implications for teaching strategies in the Informatics department. If these differences are ignored, there is a great potential to hinder teaching effectiveness, especially in classes that require understanding logical concepts and the application of technical practices, such as programming or data analysis. In this context, teachers can adapt their teaching approach by identifying the most suitable method for each cluster, so that it can embrace all students in a more inclusive way. Adjustments to teaching strategies based on these segmentation outcomes not only contribute to improved student understanding, but also to an increase in their motivation and learning outcomes in the long run.

Teaching Strategies by Student Learning Cluster




Cluster	Dominant Learning Style	Recommended Teaching Strategies	Supporting Media/Methods
 Cluster 0	Visual	Prefers diagrams and visual cues	Podcasts, audio notes, structured texts
 Cluster 1	Auditory & Read/Write	Interactive lectures, group discussions and writing tasks	Podcasts, audio notes, structured texts
 Cluster 2	Kinesthetic	Project-based learning, simulations, live labs	Virtual lab, coding practice case studies

Figure 8. Visualization of learning strategies based on the results of student learning style segmentation using the K-Means algorithm.

The findings of this research on the learning style of Informatics students support the results of previous studies that have used data mining techniques to explore student learning behavior. Research by (Safitri et al., 2022) shows that the use of clustering techniques, including K-Means, can help identify patterns in student learning behavior, in this context increasing student engagement in the learning process (Safitri et al., 2022) By understanding the differences in learning styles, lecturers can design more effective teaching materials, creating a more interactive and engaging learning environment.

Objectively mapped learning style mapping serves as a basis for lecturers to design more inclusive learning strategies. The segmentation techniques adopted in this study made it possible to take advantage of the uniqueness of each cluster in their teaching approach. For example, the use of visual media can be optimized for students in the visual cluster, while active discussions are very beneficial for the auditory cluster, and the simulation of practice is appropriate for the kinesthetic cluster (Aitdaoud et al., 2023) The application of this method not only increases student engagement, but also facilitates in-depth understanding, especially in the context of courses that require conceptual and applicative understanding, such as in the field of Informatics (Safitri et al., 2022)

Finally, it is important to note that this learning style mapping has broader implications for building a learning ecosystem that is adaptive and responsive to students' cognitive needs. This approach encourages the development of more flexible and dynamic curriculum and teaching methodologies. By understanding the different characteristics and learning patterns, educational institutions can design programs that focus not only on knowledge transfer, but also on the development of skills and positive attitudes towards long-term learning, which are expected to improve students' academic outcomes in the long run (Shafiq et al., 2022)

6. Conclusion

This study shows that the K-Means clustering method is effective in grouping students based on the learning style of the VARK model, resulting in three main clusters with different learning tendencies: visual, auditory–reading/writing combination, and kinesthetic. This segmentation provides a clear picture of the diversity of learning preferences of Informatics students and can be used as a basis for designing more adaptive teaching

strategies. These findings confirm the importance of data-driven approaches in supporting more personalized, relevant, and impactful learning to increase student participation and understanding.

7. Suggestion

Based on the results of the research, it is suggested that lecturers and study program managers begin to consider the results of learning style segmentation as a basis for designing learning strategies, preparing modules, and selecting teaching methods that are more in line with student characteristics. The use of clustering algorithms such as K-Means can be integrated in a learning evaluation system on a regular basis to obtain an overview of the dynamics of learning preferences that may change over time. Further research is expected to develop a similar approach with a wider population across study programs and use alternative algorithms such as DBSCAN or Hierarchical Clustering to obtain more comprehensive results.

References

- Agha, D., Meghji, A. F., & Bhatti, S. (2023). Clusters of success: Unpacking academic trends with K-Means clustering in education. *Vfast Transactions on Software Engineering*. <https://doi.org/10.21015/vtse.v11i4.1633>
- Aishah Noor, S. N., & Amri Ramly, M. K. (2023). Bridging learning styles and student preferences in construction technology education: VARK model analysis. *International Journal of Academic Research in Progressive Education and Development*. <https://doi.org/10.6007/ijarped/v12-i3/19313>
- Aitdaoud, M., Namir, A., & Talbi, M. (2023). New pre-processing approach based on clustering users' traces according to their learning styles in Moodle LMS. *International Journal of Emerging Technologies in Learning (ijET)*. <https://doi.org/10.3991/ijet.v18i07.37635>
- Akbari, G., & Kerlooza, Y. Y. (2018). Peningkatan hasil cluster menggunakan algoritma dynamic K-Means dan K-Means binary search centroid. *Jurnal Tata Kelola dan Kerangka Kerja Teknologi Informasi*. <https://doi.org/10.34010/jtk3ti.v4i1.1395>
- Amanian, S., Pouyesh, V., Bashiri, Y., Snelgrove, S., & Vaismoradi, M. (2020). Comparison of the conceptual map and traditional lecture methods on students' learning based on the VARK learning style model: A randomized controlled trial. *Sage Open Nursing*. <https://doi.org/10.1177/2377960820940550>
- Beldar, P. R., Pardeshi, M., Rakhade, R., & Mene, S. (2023). Analysis of clusters with Indian patent data using different word embedding techniques. *SFS*. <https://doi.org/10.53555/sfs.v10i3.2110>
- Bhayangkara, A. N., Firdaus, D. B., & Diyan Pratiwi, T. R. (2019). VARK questionnaire online platform as a spearhead for the effectiveness of styles and methods of teaching teachers. <https://doi.org/10.2991/coema-19.2019.11>
- Chandrasekera, T., Hosseini, Z., Perera, U., & Hyscher, A. B. (2024). Generative artificial intelligence tools for diverse learning styles in design education. *International Journal of Architectural Computing*. <https://doi.org/10.1177/14780771241287345>
- Delima, N., & Budianingsih, Y. (2020). Gaya belajar dan mathematics self-concept terhadap minat akademik mahasiswa. *Teorema Teori Dan Riset Matematika*. <https://doi.org/10.25157/teorema.v5i1.3296>
- Dinata, R. K., Novriando, H., Hasdyna, N., & Retno, S. (2020). Reduksi atribut menggunakan information gain untuk optimasi cluster algoritma K-Means. *Jurnal Edukasi dan Penelitian Informatika (Jepin)*. <https://doi.org/10.26418/jp.v6i1.37606>
- Fitri, A., & Solihati, N. (2023). Analisis penerapan pembelajaran diferensiasi proses melalui gaya belajar siswa pada materi menulis laporan hasil observasi. *Semantik*. <https://doi.org/10.22460/semantik.v12i2.p221-232>
- Gede Sarasvananda, I. B., Wardoyo, R., & Sari, A. K. (2019). The K-Means clustering algorithm with semantic similarity to estimate the cost of hospitalization. *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*. <https://doi.org/10.22146/ijccs.45093>
- Habibah, N., Rahmawati, S., & Sayekti, A. (2019). Pengaruh gaya belajar terhadap prestasi mahasiswa generasi Z di perguruan tinggi. *Perspektif Ilmu Pendidikan*. <https://doi.org/10.21009/pip.332.2>
- Hao, Y., Hao, S., Andersen-Nissen, E., Mauck, W. M., Zheng, S., Butler, A., Lee, M., Wilk, A. J., Darby, C. A., Zager, M., Hoffman, P., Stoeckius, M., Papalexi, E., Mimitou, E. P., Jain, J., Srivastava, A., Stuart, T., Fleming, L. M., Yeung, B. Z., ... Satija, R. (2021). Integrated analysis of multimodal single-cell data. *Cell*. <https://doi.org/10.1016/j.cell.2021.04.048>
- Hasanun, Abdullah, D., & Daud, M. (2023). Pengembangan sistem e-learning Politeknik Negeri Lhokseumawe dengan model VARK. *Jurnal Informasi dan Teknologi*. <https://doi.org/10.60083/jidt.v5i4.380>
- Hernandez, J., Vasan, N., Huff, S., & Melovitz-Vasan, C. (2020). Learning styles/preferences among medical students: Kinesthetic learner's multimodal approach to learning anatomy. *Medical Science Educator*. <https://doi.org/10.1007/s40670-020-01049-1>

- Hervina, W. (2021). Optimalisasi kebutuhan murid dan hasil belajar dengan pembelajaran berdiferensiasi. *Perspektif Ilmu Pendidikan*. <https://doi.org/10.21009/pip.352.10>
- Hilman, I., Akmal, R., & Nugraha, F. (2023). Analisis gaya belajar peserta didik melalui assessment diagnostik non-kognitif pada pembelajaran diferensiasi di sekolah dasar. *Naturalistic Jurnal Kajian Penelitian Pendidikan Dan Pembelajaran*. <https://doi.org/10.35568/naturalistic.v8i1.3911>
- Ilahana, V. T., & Rachmawati, E. (2022). Public perception about virtual tourism for conservation area promotion. *Tourism and Sustainable Development Review*. <https://doi.org/10.31098/tsdr.v3i1.58>
- Irawati, I., Ilhamdi, M. L., & Nasruddin, N. (2021). Pengaruh gaya belajar terhadap hasil belajar IPA. *Jurnal Pijar Mipa*. <https://doi.org/10.29303/jpm.v16i1.2202>
- Irennada, Solichin, A., & Brotosaputro, G. (2022). Klasifikasi gaya belajar mahasiswa berdasarkan garis telapak tangan menggunakan convolutional neural network. *Jurnal Nasional Pendidikan Teknik Informatika (Janapati)*. <https://doi.org/10.23887/janapati.v11i3.53721>
- Irmanda, H. N., Santoni, M. M., & Astriratma, R. (2020). Case based reasoning untuk menentukan gaya belajar mahasiswa. *Informatik Jurnal Ilmu Komputer*. <https://doi.org/10.52958/iftk.v15i3.1293>
- Ismail, S. M., & Azlan Haniff, W. A. (2020). Education 4.0: The effectiveness of VARK learning style towards actualising Industrial Revolution 4.0. *Journal of Educational and Social Research*. <https://doi.org/10.36941/jesr-2020-0045>
- Jahring, J. (2019). Preferensi modalitas belajar mahasiswa angkatan 2016 program studi pendidikan matematika Universitas Sembilanbelas November Kolaka. *Square Journal of Mathematics and Mathematics Education*. <https://doi.org/10.21580/square.2019.1.1.4039>
- Kanojiya, A. (2023). The learning style preferences of the undergraduate computer applications and IT students. *International Journal of Scientific Research in Engineering and Management*. <https://doi.org/10.55041/ijsem18006>
- Karim, M. R., Asaduzzaman, A. K. M., Kabir Talukder, M. H., Alam, K. K., Haque, F., & Khan, S. J. (2019). Learning style preferences among undergraduate medical students: An experience from different medical colleges of Bangladesh. *Bangladesh Journal of Medical Education*. <https://doi.org/10.3329/bjme.v10i2.44640>
- Karim, Md. R., Kabir Talukder, M. H., Mondol, R. U., Ghose, R. K., & Iftekhar Hossain, M. M. (2023). Learning styles of undergraduate medical students and their relation with preferred teaching-learning methods. *Taj Journal of Teachers Association*. <https://doi.org/10.3329/taj.v35i2.63690>
- Khamphaya, T., Pouyfung, P., & Yimthiang, S. (2022). Enhancing toxicology achievement by the VARK and the GRSLSS-mixed models in team-based learning. *Frontiers in Public Health*. <https://doi.org/10.3389/fpubh.2021.732550>
- Kholidin, N., Suarna, N., & Prihartono, W. (2024). Segmentasi gaya hidup mahasiswa menggunakan algoritma K-Means clustering. *Jeliku (Jurnal Elektronik Ilmu Komputer Udayana)*. <https://doi.org/10.24843/jlk.2023.v12.i03.p26>
- Kurniawan, D., & Riswanto, A. (2023). Perubahan pendidikan sosial memaknai lahirnya produk hukum baru. *Jurnal Konseling Pendidikan Islam*. <https://doi.org/10.32806/jkpi.v4i1.301>
- Leveraging TF-IDF Matrix for Document Clustering With K-Means Algorithm. (2024). *International Journal of Scientific Research and Modern Technologies*. <https://doi.org/10.38124/ijsrmt.v3i10.61>
- Maidin, S., Shahrum, M. A., Qian, L., Rajendran, T. K., & Ismail, S. (2023). Effective blended learning model selection based on student learning style using analytic hierarchy process for an undergraduate engineering course. *International Journal of Engineering*. <https://doi.org/10.5829/ije.2023.36.12c.13>
- Mayasari, E. D., Evanjeli, L. A., Tri Anggadewi, B. E., & Purnomo, P. (2021). Elementary school students' mental health during the Corona virus pandemic (COVID-19). *Journal of Psychology and Instructions*. <https://doi.org/10.23887/jpai.v5i1.34935>
- Michalowski, M., Wilk, S., Michalowski, W., O'Sullivan, D., Bonaccio, S., Parimbelli, E., Carrier, M., Gal, G. Le, Kingwell, S., & Peleg, M. (2021). A health eLearning ontology and procedural reasoning approach for developing personalized courses to teach patients about their medical condition and treatment. *International Journal of Environmental Research and Public Health*. <https://doi.org/10.3390/ijerph18147355>
- Mohajan, H. (2020). Quantitative research: A successful investigation in natural and social sciences. *Journal of Economic Development Environment and People*. <https://doi.org/10.26458/jedep.v9i4.679>
- Nabilla, P., Saputra, Muh. F., & Saputra, R. A. (2022). Perbandingan ruang warna RGB, HSV dan YCbCr untuk segmentasi citra ikan kembung menggunakan K-Means clustering. *Jati (Jurnal Mahasiswa Teknik Informatika)*. <https://doi.org/10.36040/jati.v6i2.4770>
- Newton, P. M., & Salvi, A. (2020). How common is belief in the learning styles neuromyth, and does it matter? A pragmatic systematic review. *Frontiers in Education*. <https://doi.org/10.3389/feduc.2020.602451>
- Nugraha, A. A., & Budiyanto, U. (2022). Adaptive e-learning system berbasis VARK learning style dengan klasifikasi materi pembelajaran menggunakan K-NN (K-Nearest Neighbor). *Technomedia Journal*. <https://doi.org/10.33050/tmj.v7i2.1900>
- Rachmatika, R., & Bisri, A. (2020). Perbandingan model klasifikasi untuk evaluasi kinerja akademik mahasiswa. *Jurnal Edukasi dan Penelitian Informatika (Jepin)*. <https://doi.org/10.26418/jp.v6i3.43097>

- Safitri, S. N., Setiadi, H., & Suryani, E. (2022). Educational data mining using cluster analysis methods and decision trees based on log mining. *Jurnal Resti (Rekayasa Sistem dan Teknologi Informasi)*. <https://doi.org/10.29207/resti.v6i3.3935>
- Shafiq, D. A., Marjani, M., Ariyaluran Habeeb, R. A., & Asirvatham, D. (2022). Student retention using educational data mining and predictive analytics: A systematic literature review. *IEEE Access*. <https://doi.org/10.1109/access.2022.3188767>
- Shahapure, K., & Nicholas, C. (2020). Cluster quality analysis using silhouette score. <https://doi.org/10.1109/dsaa49011.2020.00096>
- Shutaywi, M., & Kachouie, N. N. (2021). Silhouette analysis for performance evaluation in machine learning with applications to clustering. *Entropy*. <https://doi.org/10.3390/e23060759>