**International Journal of Environmental Sciences**
ISSN: 2229-7359
Vol. 11 No. 14s, 2025
https://www.theaspd.com/ijes.php

# A Journey of STEM Education Model towards VBSTEM to UHV-STEM: A Clustering Based Predictive Analysis

**Dheeraj Kumar Singh[1] and Narender Kumar[2]**
[1, 2]Department of Computer Science, Doon University, Dehradun, Uttarakhand-248001, India

## ABSTRACT
*Promoting sustainable and holistic education assisted with sustainable development goals (SDG) requires integration of value based (Vb) education such as Universal Human Values (UHV) with STEM (science, technology, engineering, and mathematics). Current study explores the transition from standard STEM education towards VbSTEM to UHV-STEM, with highlighting the importance of value-based education in producing responsible and ethical professionals. The study validates and justifies the effectiveness of UHV-STEM integration using arrange of clustering approaches on educational data. By analyzing student performance, course, subject selection, programme, and pedagogical alignment, the study identifies patterns and relationships that highlight UHV's impact on STEM education as value based education. To determine the effectiveness of UHV-STEM, data is aggregated using clustering techniques such as K-Means, DBSCAN, and more. The findings bolster the case for integrating UHV into STEM education and fostering more inclusive, morally and culturally driven learning atmosphere.*

## 1. INTRODUCTION

Educational data mining (EDM) enables the following: predicting student performance, analyzing pedagogy, selecting relevant programme, subjects, and designing courses that are tailored to each individual student (Baker & Yacef, 2009; Díaz et al., 2025).

One of the biggest issues facing education today is the ability to analyze student performance accurately enough to offer targeted support and intervention. Student learning preferences, academic standing, and other relevant criteria can all be taken into account when grouping those using clustering methods such as OPTICS, Affinity Propagation, and others.

Looking at these clusters and identifying patterns that suggest potential areas of academic strength or weakness might help teachers design tailored interventions to help students perform better (DAS et al., 2025; Khan et al., 2014; Su & Wu, 2021; Xia, 2020).

To ascertain demand and create curricula that align with students' interests, clustering algorithms are employed in course prediction analysis for STEM / STE(A)M (Science, Technology, Engineering, (Arts,) Mathematics) courses (Choi et al., 2017; Kiyani, 2025; Liao, 2016; Shin & Shim, 2021; Teixeira et al., 2025; Wong et al., 2025 ).

Teachers can design STEM courses that are current, interesting, and aligned with students' future jobs by using clustering algorithms to assess data on students' interest in STEM/STEAM disciplines, career goals, and market trends.

By providing students with the knowledge and abilities needed to thrive in the twenty-first century, secure physical facilities, and the opportunity to capitalize on attractive STEM careers, this approach raises the quality of life for students (Cetto et al., 2000; Webber et al., 2025). But the stress, fear, and anxiety that the students are feeling are insufficient for it to handle (Gaur et al., 2010).

To generate individuals who are not just physically and academically capable but also ethically and cognitively mature, institutions must teach Universal Human Values (UHV) (Gaur et al., 2010; Singh & Kumar, 2024).

Teachers can impart values to children that are essential for creating a sustainable and inclusive society, such as trust, gratitude, reverence, compassion, integrity, and respect for cultural diversity, by including UHV into STEM/STEAM courses (Singh & Kumar, 2024).

In addition to ensuring that students have the attitudes and values necessary to be responsible global citizens, collaborative working culture across all places and institutions, a holistic approach to education guarantees that students are ready for success in both the classroom and the job.

(Gaur et al., 2010) assert that UHV has the capacity to radically alter the environment, universal society, family, community, and individual.

In conclusion, integrating Universal Human Values with STEM/STEAM education, or UHVSTEM / UHVSTEAM, has the potential to significantly transform the educational landscape (Singh & Kumar, 2024). Even value based education in STEM termed as VbSTEM (Singh & Kumar, 2025) played an important role in holistic and sustainable living.

This analysis is made possible by the application of clustering algorithms in educational data mining. Using a variety of tools and techniques, educators can design customized curricula and programs, assess student performance, and spread ideas that are essential for long-term, sustainable development. This comprehensive method of instruction enhances children's growth and well-being in addition to their academic performance, giving them the empathy and self-assurance they need to take on new challenges.

## 2. LITERATURE REVIEW

Clustering algorithms are becoming more and more popular in the field of education, particularly in the domains of student performance analysis and instruction. Three significant areas in which clustering is employed in education are course planning, curriculum design, and course prediction as well predictive analysis (Antonenko et al., 2012; Chakrabarti et al., 2006; Durachman & Rahman, 2025; Kord et al., 2025; Regueras et al., 2019; Basha et al., 2025).

Teachers can look into unique learning routes by grouping students based on their interests, academic standing, and limitations. Furthermore, clustering algorithms can help teachers identify students who might need extra attention by accurately estimating future academic progress. Many characteristics, such as family socioeconomic position, psychology, behavior, and demographic data, have a substantial impact on academic performance and course selection (Batool et al., 2023; Issah et al., 2023; Kukkar et al., 2024; Liu et al., 2022; Sangsawang & Yang, 2025; Smeets et al., 2025).

## 3. FACTORS IMPACTING STUDENTS' PERFORMANCE

Apart from the previously described research, there exist multiple other variables that may impact students' academic achievement, such as the choice of subject, program, and courses, as well as their projections and evaluation (Table 1), which are discussed upon subsequently:

**Table 1:** success determinants in addition to the courses, subjects, and programs

| Qualitative Parameters | Quantitative Parameters |
|---|---|
| Faculty Expertise and Engagement | Financial Aid and Scholarships |
| Learning Environment | Class Size |
| Peer Collaboration and Networking | Student-to-Teacher Ratio |
| Cultural and Social Inclusion | Availability of Learning Resources |
| Flexibility of Program | Number of Internship Placements |
| Career Services | IT Infrastructure Quality and Support Services |
| Learning Styles Accommodation | Number of Extracurricular Opportunities |
| Practical Experience | Scholarship Amounts |
| Community Engagement | Percentage of Accredited Programs |
| Social and Emotional Support | Global Opportunities (e.g., study abroad programs) |
| Alumni Network | Percentage of Alumni Employment Success |
| Government or Industry Ties | Number of Government/Industry Partnerships |
| Environmental Factors | Local Economic Indicators |
| Academic Rigor | Graduation Rates and Academic Success Metrics |

| | |
|---|---|
| Technological Access and Support | Percentage of Technology-Enhanced Courses |
| Availability of Learning Resources | Global Opportunities |
| Sustainability and Ethical Considerations | Program Duration |
| Cultural Relevance | Number of Elective Courses |
| Extracurricular Opportunities | Number of Research Opportunities |

These traits may be qualitative or quantitative in nature, according to studies by ( Babu et al., 2024; Babu & Satya, 2024; Bansal et al., 2023; ;Barr & Luo, 2025; Crisp et al., 2009; Gasiewski et al., 2012; Gaur et al., 2010; ; Salem & Shaalan, 2025; Williams & Williams, 2011). In addition to the previously indicated variables, considering all of the aforementioned data may assist in gaining a greater understanding of students' choices of courses, subjects, and programs.

## 4. PROPOSED WORK

Finding patterns is the main goal of data mining, also known as knowledge discovery in databases (Agrawal et al., 1993). To be more precise, data mining techniques are used in educational data mining, or EDM, to find trends within the educational domain. Patterns discovered with educational data mining technologies will revolutionize research and growth projection for students (López-Meneses et al., 2025; Romero & Ventura, 2007). Ultimately, EDM has the potential to predict economic and societally beneficial online and offline education through colleges, universities, and other academic establishments. Among the most widely used applications of EDM are learning objectives, course completion rates, student identification, curriculum building, efficient test-taking, and performance prediction. It also aids in course selection, analysis, and the reduction of student dropout rates.

### 4.1 Existing Algorithms to be used

For the purpose of discovering patterns for predictive analysis, clustering is a helpful unsupervised learning technique (Asif et al., 2017; Durairaj & Vijitha, 2014; Kalita et al., 2025; Peña-Ayala, 2014; Suciati et al., 2023). Mean-Shift, Agglomerative Hierarchical Clustering, Mini-Batch K-Means, BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies), OPTICS (Ordering Points To Identify the Clustering Structure), DBSCAN (Density-Based Spatial Clustering of Applications with Noise), and K-Means A few clustering methods that can be applied to course, subject, and program building in educational environments (Ankerst et al., 1999; Kerimbayev et al., 2025; Khan et al., 2014; Peng et al., 2018; Sasirekha & Baby, 2013; Wang et al., 2018; Wu & Yang, 2007;Wu & Ouyang, 2025).

A confusion matrix or matching matrix that correlates to each strategy can be produced to evaluate specifics such as efficiency and accuracy. The confusion matrix's findings provide light on how well clustering algorithms may be used to organize courses based on their characteristics. Teachers can use these data to improve students' overall learning experiences, course recommendations, and curriculum design.

### 4.2 Proposed Hybrid Common Density Based K-Means Algorithm

**1. Initial Clustering with DBSCAN**

a. DBSCAN identifies dense regions as clusters and marks sparse, low-density points as noise (label = 1).

b. Ideal for detecting arbitrarily shaped clusters and filtering out outliers.

**2. Data Segregation**

a. Split dataset into:

i. Core Points: Assigned to valid DBSCAN clusters (label >=0)

ii. Noise Points: Unclustered outliers (label = -1)

**3. K-Value Selection for K-Means**

a. Set k as:

i. Number of DBSCAN clusters (k = k_db)

ii. Or use a tuning method (e.g. elbow method, silhouette score) for optimal k.

**4. K-Means Integration Strategies:**

**a. Option A – Refine Core:**
Apply K-means to DBSCAN core points to improve intra-cluster compactness.

**b. Option B – Assign Noise:**
Apply K-Means to noise points to group previously unclustered data.

**c. Option C – Re-cluster Entire Set:**
Run K-Means on the full dataset using DBSCAN cluster centroids as initial centers for better convergence.

**5. Final Labeling:**

a. Combine or update cluster labels from DBSCAN and KMeans based on the selected option.

b. Results in improved clustering accuracy, robustness, and effective handling of outliers.

The integration of DBSCAN and K-Means combines the strengths of both: DBSCAN effectively detects arbitrary-shaped clusters and removes noise, while K-Means ensures compact, well-separated clusters. Together, they improve clustering accuracy, handle outliers better, and reduce sensitivity to initialization. This hybrid approach enhances robustness and performance, especially in complex datasets with varying density and unclear boundaries.

## 5. RESEARCH METHODOLOGY

In contrast, research indicates that UHV education can more effectively address attaining harmony at the societal, family, individual, natural, and existential levels of human existence as well more efficient to understanding all orders such as material, bio, animal, and human order (Gaur et al., 2010). A qualitative research design was used for this investigation. The Train to Trainers program required teachers to teach UHV curriculum for roughly eighteen hours, and students were required to teach for eighteen hours as well. Second, using Google Form Analytics, research queries based on the Likert five-point scale were created with the constructs "Strongly Agree," "Agree," "Undecided," "Disagree," and "Strongly Disagree" (Armstrong, 1987).

As previously stated in the research, a confusion matrix was ultimately created by utilizing a number of clustering techniques. Courses that, in part, fit into the current educational system have also been identified by instructors and students in the arts and sciences. The following are the designated research questions:

**RQ1.** IS UHV incorporation with current education will lead students towards Happiness?

**RQ2.** IS only STEM (Science, Technology, Engineering, and Mathematics) education will lead Harmony in Human being?

**RQ3.** Is addition of UHV education with STEM education will lead Harmony in Human being?

**RQ4.** If Value Education cell open-up in your University, would you ready to work as Volunteer for it?

**RQ5.** Would you like to work as Volunteer for UHV?

**RQ6.** Would you like to share UHV with school children?

**RQ7.** Is UHV Based Education - Sanskar will reduce the crime level of society?

**RQ8.** Is UHV Based 'Education - Sanskar' delivered to students and society will reduce the corruption level?

**RQ9.** IS UHV based education delivered to students, will it reduces the stress level of students?

**RQ10.** Will UHV based education be holistic and sustainable education approach.

Knowing what is correct is characterized as "education" or to see the reality as it is known as "education" by (Gaur et al., 2010), whereas "sanskar" refers to living accordingly. To anticipate a research framework or pedagogical framework based on Universal Human Values (UHV) for STEM (science, technology, engineering, and mathematics) or NON-STEAM (science + arts) subjects, many important factors can be considered.

Curriculum integration, instructional strategy selection, evaluation of value integration, professional development for educators, facilitators, and co-explorers, stakeholder interaction, and instructional strategy selection that advances UHV application and understanding in STEM and non-STEAM fields are all important facets of education.

The adoption of this value-based collaborative approach would ensure the relevance and efficacy of the framework while fostering complementarity, as per the findings of (Singh & Kumar (2024).

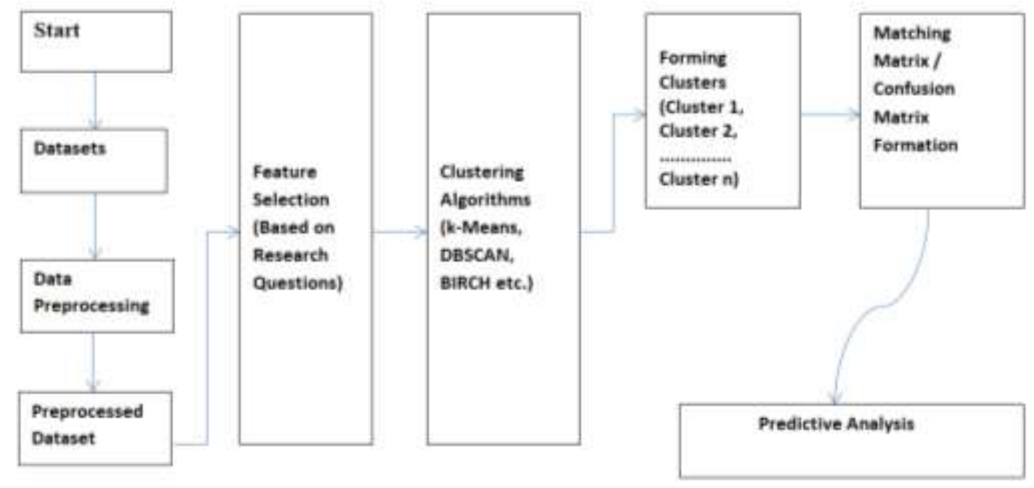


**Figure 1:** Methodology employed in the clustering-based educational framework

Figure 1 shows the methodology adopted for this research work. When examining and enhancing research frameworks and curricula based on Universal Human Values (UHV) and targeted at STEM (science, technology, engineering, and mathematics) or NON-STEAM (non-science, technology, and arts) disciplines, clustering algorithms are a helpful tool. Gather data about stakeholder involvement, research and evaluation, assessment strategies, professional growth, and core values. Every data unit needs to match a specific framework component (Feldman-Maggor et al., 2021; Hongell, 2025; Kurday & Vladova, 2025).

To make the clustering procedure easier, choose pertinent features from the dataset (Hamdipour et al., 2025; Parhizkar et al., 2023; Shukla & Patel, 2025). Apply clustering methods using the customized data. These algorithms will merge similar data points based on the feature values of each individual data point.

A framework for a Value based or UHV-based STEM / STEAM / NON-STEAM course, subject, program, or instruction can be developed, evaluated, and implemented using cluster analysis approaches. Make a comparison between the proposed framework and the existing one and transmit it to the appropriate parties for validation. Make necessary adjustments to the framework to ensure that it is appropriate, workable, practical, and also complies with value based as well UHV standards.

### 5.1 Performance Metrics:

To accomplish the methodology's ultimate objective, the confusion matrix or matching matrix and its associated attributes (Accuracy, Precision, Recall, F1-Score, and Specificity) are required (Xia, 2020; Kord et al., 2025). These parameters are outlined below:

**True Positive (TP):** The number of precise predictions indicating a positive occurrence.

**True Negative (TN):** The number of accurately predicted occurrences that are negative.

**False Positive (FP):** incorrectly projected as positive when it is actually negative.

**False Negative (FN):** incorrectly understood to be negative when it is actually positive.

Accuracy = (TP + TN) / (TP + TN + FP + FN) (Formula 1)

Precision = TP / (TP + FP) (Formula 2)

Recall (Sensitivity) = TP / (TP + FN) (Formula 3)

F1 Score = 2 * (Precision * Recall) / (Precision + Recall) (Formula 4)

Specificity = TN / (TN + FP) (Formula 5)

Feature selection, data preparation, normalization, cluster analysis, framework categorization, and performance metric validation are the important steps in the technique.

## 6. RESULT ANALYSIS

### 6.1 Results Based on Existing Algorithms:

This section presents the findings from a few particular study phases on the relevant issues. Several clustering techniques have been identified and proven through educational data mining to evaluate the dataset for further study. To predict the course UHV-STEM / UHVSTEM, such clustering techniques include K-Means, DBSCAN, BIRCH, Affinity Propagation, Mean-Shift, OPTICS, Agglomerative Hierarchy, and Mini-Batch K-means.

For validation purposes, the association between different clustering approaches and confusion matrix parameters such as precision, recall, specificity, and sensitivity has been studied.

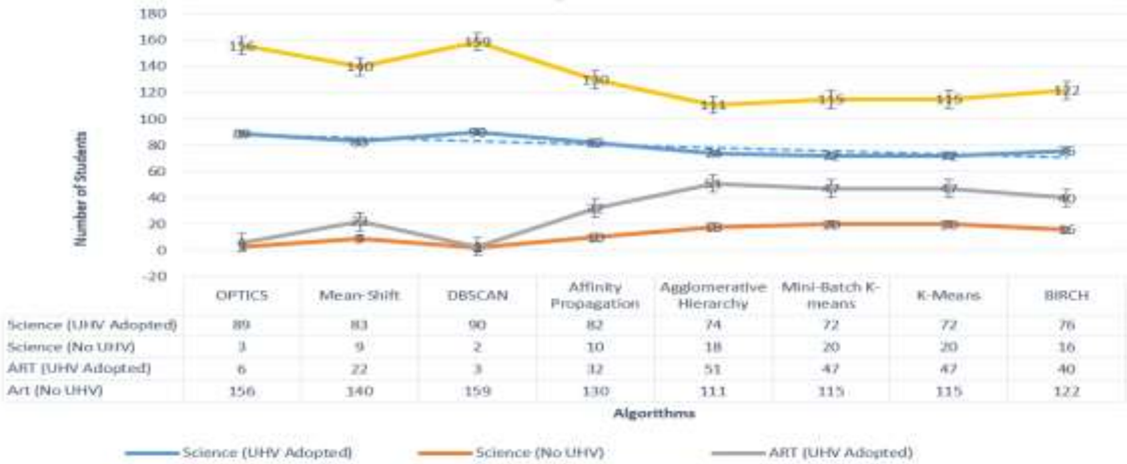


**Figure 2:** Results of the ML Model using Clustering Feature Selection Algorithms

The adoption rate of UHV by educators and learners in the art stream is relatively low across all clustering algorithms, as the confusion matrix in Figure 2 shows, whereas it is highly high among those in the scientific stream. For all science faculty members and students, the rates of UHV adoption are as follows: The following results were attained using the algorithms for clustering: Mean-Shift scored 90.22%, Affinity Propagation scored 89.13%, Agglomerative Hierarchy scored 80.43%, Mini-Batch K-

Means scored 78.26%, K-Means scored 78.26%, and BIRCH scored 82.61%, while OPTICS scored 96.74%.

As a result, the Mini-Batch K-Means and K-Means algorithms have decided the lowest predictive analysis rate for UHV, while the DBSCAN clustering approach has found the greatest. By creating the confusion matrix, more research has been done on the various classification analysis-related criteria, such as Precision, Recall, F1-Score, and Specificity, for the predictive analysis of the results pertaining to the produced clusters. It is feasible to ascertain the proportion of teachers who enroll in UHV courses relative to students pursuing science and the arts since two clusters specifically designed for this study were established for these learners.

Figure 3's representation facilitates comprehension of the real accuracy calculations. The results show that the Agglomerative Hierarchy method and the Mini-Batch K-Means algorithm produce the best results. This implies that the K-Means algorithm may be the most accurate predictive analytic technique, even though DBSCAN produces the least accurate results.

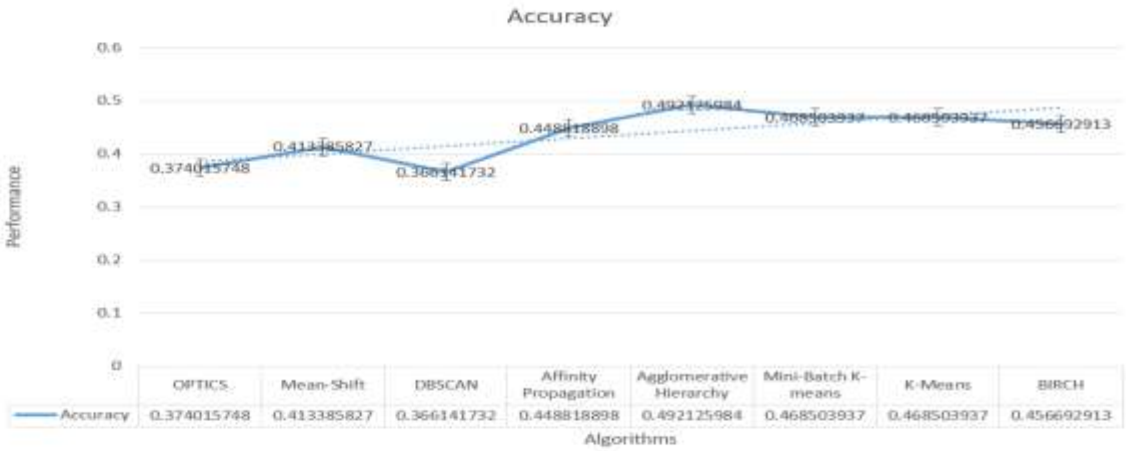


**Figure 3:** Evaluating the degree of accuracy related to various clustering techniques

On the other hand, DBSCAN produces the least precision. Figure 4 provides a visual representation that makes the true precision computation understandable. It seems that the Affinity Propagation strategy comes in second for precision, and the Agglomerative Hierarchy method produces the best results overall.

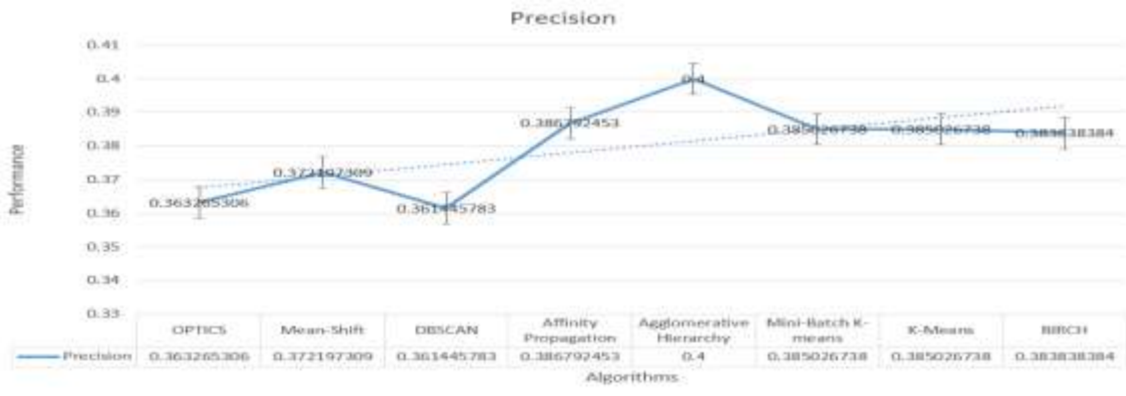


**Figure 4:** computing the precision level in connection to different clustering algorithms

An understanding of the recall computation process can be gained by examining the depiction shown in Figure 5. OPTICS and DBSCAN clearly produce the highest recall values, respectively. In terms of recall, Mean-Shift is the most effective predictive analysis technique. Ultimately, it is clear that every algorithm under investigation had recall values more than 78%. It suggests that participants in science are considerably more sensitive to the adoption of UHV than participants in the arts. Thus, UHV-based training is crucial in today's educational system.

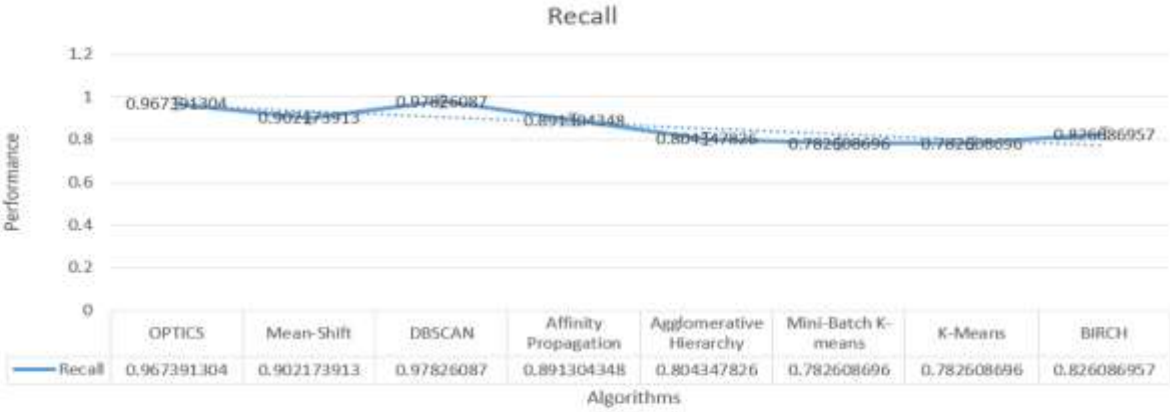


**Figure 5:** determining the recall threshold for different clustering techniques

Figure 6 provides a picture of the precise F1-Score computation. The Affinity Propagation method clearly performs better than the Agglomerative Hierarchy algorithm in terms of F1-Score; OPTICS, on the other hand, is the optimal algorithm for predictive analysis; and the Mini-Batch K-Means approach produces the lowest F1-Score.

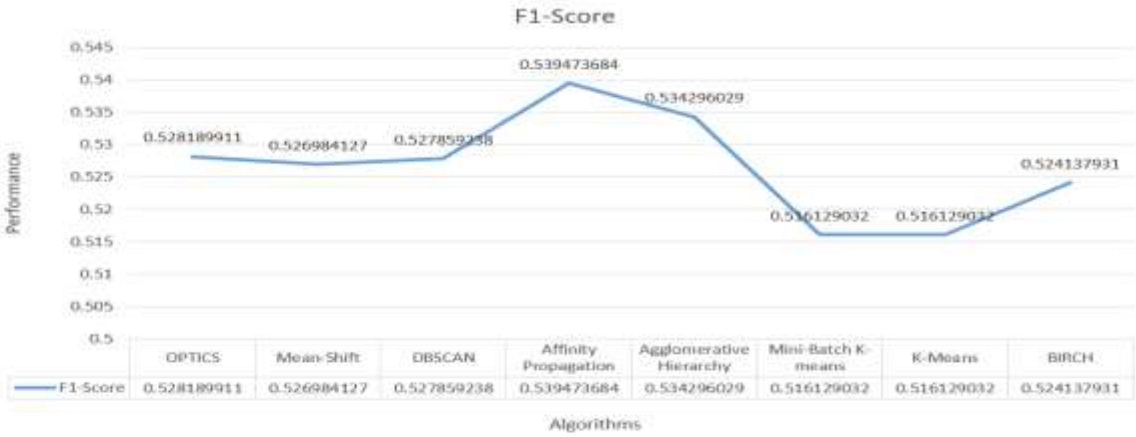


**Figure 6:** figuring out the F1-Score threshold for different clustering techniques

The figure in Figure 7 helps to explain the correct specificity computation. It is clear that the Agglomerative Hierarchy approach produces the highest specificity, whereas the DBSCAN clustering process produces the lowest.

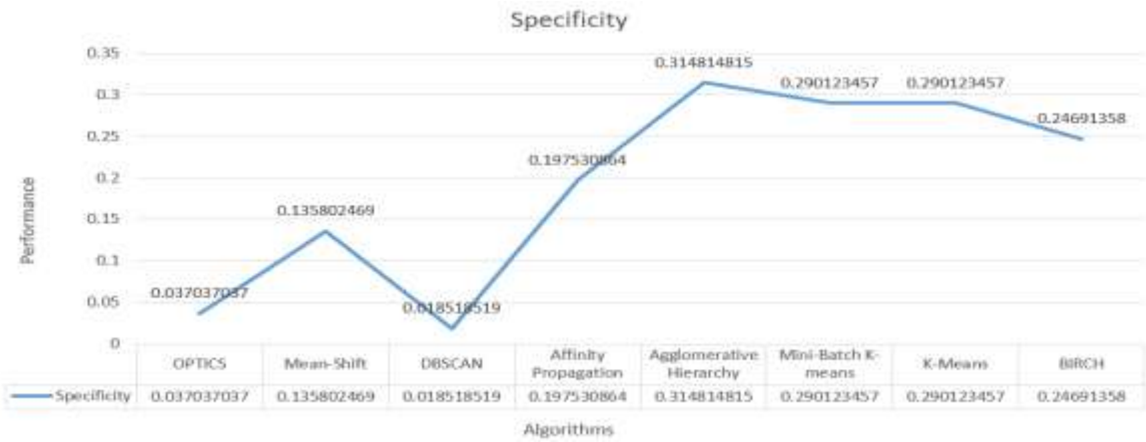


**Figure 7:** figuring out the specificity level connected to different clustering algorithms

Finally, Table 2 lists a number of cluster-based categorization assessment metrics that may be evaluated at one place, including recall value, accuracy, precision, F1-score, and specificity.

**Table 2:** assessment metrics using clustering methods for student performance.

| Specificity | Recall | F1-Score | Precision | Accuracy | Algorithms |
|---|---|---|---|---|---|
| 0.018519 | 0.97826087 | 0.527859238 | 0.361445783 | 0.366141732 | DBSCAN |
| 0.037037 | 0.967391304 | 0.528189911 | 0.363265306 | 0.374015748 | OPTICS |
| 0.135802 | 0.902173913 | 0.526984127 | 0.372197309 | 0.413385827 | Mean-Shift |
| 0.197531 | 0.891304348 | 0.539473684 | 0.386792453 | 0.448818898 | Affinity Propagation |
| 0.246914 | 0.826086957 | 0.524137931 | 0.383838384 | 0.456692913 | BIRCH |
| 0.314815 | 0.804347826 | 0.534296029 | 0.4 | 0.492125984 | Agglomerative Hierarchy |
| 0.290123 | 0.782608696 | 0.516129032 | 0.385026738 | 0.468503937 | K-Means |
| 0.290123 | 0.782608696 | 0.516129032 | 0.385026738 | 0.468503937 | Mini-Batch K-means |

Excluding this study the separate study has been done for only science and arts students as well teachers who are only girls and who are only boys the almost same outcome received after applying the these various clustering algorithms. Ultimately, it has been seen in every situation that sensitivity towards implementation of UHV was very high among Science fertility.

### 6.2 Result based on Proposed Hybrid Common Density Based K-Means Algorithm

Introducing a new pedagogy, curriculum, course, subject, programme are always the challenging task for everyone including school teachers, professors, educationist, institutions as well to the Universities also. But still it is being evident, if there is anything which have sensitivity towards generations for learning, understanding right, and rightly living that pedagogy have to be developed always. In the quantitative analysis, if any course, subjects, or programme have its reacall value means sensitivity greater than the 50 percent of the total observation, than it is always concluded that this have to be implemented in the complete education system. Here through our proposed algorithm more than 75% sensitivity (recall) have been identified through using confusion matrix (matching matrix) analysis. Definitely, lot of existing algorithms are there, mentioned in Table 2, have more than 90% recall value. So, our proposed algorithm not claim that it is the best one, but have to consider here in this study for supporting that the UHV have to be part of the study or not. Again, it have to be mentioned here that this study is qualitative for the next generation, and quantitatively analyzed through these proposed and existing algorithms.

### 6.3 Significance of the study:

The results of this qualitative study demonstrate how sensitive teachers and students are to the adoption of value based education such as UHV. Since STEM is currently widely used in education, the paradigm for education in the modern world needs to be STEM (STEM) based on Universal Human Values (UHV) rather than merely STEM, where it is identified as SDG goals that it is the value based education and has been adopted widely in India by All India Council for Technical Education (AICTE), and University Grant Commission (UGC). Students will be able to attend cutting-edge, individualized courses and acquire values that are essential to their long-term success by combining values with STEM (VbSTEM) or UHV with STEM (UHV-STEM).

Table 3 which are provided below, help to clarify the comparison between the STEM and UHV-STEM educational models.

**International Journal of Environmental Sciences**
ISSN: 2229-7359
Vol. 11 No. 14s, 2025
https://www.theaspd.com/ijes.php

**Table 3:** A comparative analysis of the STEM and UHV-STEM educational models

| Aspect | STEM | UHV-STEM |
|---|---|---|
| **Definition** | Focuses on Science, Technology, Engineering, and Mathematics. | Integrates Universal Human Values with STEM education. |
| **Technical Proficiency** | Develops advanced technical skills crucial for innovation and problem-solving. | Balances technical proficiency with a strong emphasis on values, ensuring responsible innovation. |
| **Primary Focus** | Technical skills, problem-solving, and innovation. | Combination of technical skills and ethical, humanistic values. |
| **Economic Impact** | Drives economic growth through technological advancements and skilled workforce | Promotes sustainable economic development by aligning technological progress with societal needs. |
| **Global Competitiveness** | Enhances global competitiveness by producing experts in critical STEM areas. | Fosters a globally competitive workforce that also prioritizes ethical standards and social responsibility. |
| **Innovation and Research** | Encourages ground breaking research and technological advancements. | Supports innovation that considers long-term societal impacts and ethical considerations. |
| **Educational Rigor** | Offers a rigorous education that sharpens analytical and problem-solving skills. | Provides a rigorous education that also fosters emotional intelligence, empathy, and integrity. |
| **Social Impact** | Contributes to societal progress through scientific discoveries and new technologies. | Ensures that technological contributions are beneficial and considerate of human values, enhancing social well-being. |
| **Holistic Growth** | Focuses on developing strong technical and analytical capabilities. | Promotes holistic growth by integrating moral and ethical development with technical education. |
| **Workforce Readiness** | Prepares students to meet the demands of modern industries with specialized knowledge. | Equips students to enter the workforce with both specialized knowledge and a commitment to ethical practices. |
| **Sustainability** | Advances technology with the potential for high-impact solutions. | Encourages sustainable innovation that prioritizes the environment and human welfare. |
| **Approach of Learning** | Body-Centric, Skill Centric Approach | Self-Centric, Value Centric Approach |
| **Prime Concern / Decision** | Student Centric Leaning and Decision | Teacher Centric Learning and Decision |

Table 3 lists the key differences and similarities between STEM and UHV-STEM. It also illustrates how the latter incorporates Universal Human Values within the traditional STEM framework to promote a more comprehensive approach to education. The aim of this course is to create well-rounded individuals who not only serve as capable professionals but also ethically and socially conscious members of society.

In this case, clustering approaches are used to independently analyze the significance of UHV for educators and learners in STEM and non-STEM fields. Predicting an educational model (UHV-STEM) for a social, economic, sustainable, co-existential, holistic, and all-encompassing approach to education is the ultimate goal of this research study.

In line with the Sustainable Development Goals (SDGs) of the UN, two educational philosophies—"skill-based learning" and "value-based learning"—are essential to attaining holistic and sustainable development. ‘Skill-based learning’ or ‘STEM learning’ provides people with the practical skills required for economic growth and innovation, while 'Value-based learning' or 'UHV-STEM learning' ensures that these abilities are used in a way that promotes social equity, environmental sustainability, ethical behavior, living with definite human conduct, and ethical governance. So, this will be admirable to transform the education from only STEM to VbSTEM or ultimately to UHV-STEM / UHVSTEM.

Since Value based education is the priority of human being, so, this identified model of education UHV-STEM may be known to be as UHVSTEM / UHV-STEAM / UHVSTEAM/ Value based STEM means VbSTEM and / or Value based STEAM means VbSTEAM.

## 7. CONCLUSION AND FUTURE WORK

The study aimed to explore the potential integration of value based education perspective identified by Universal Human Values (UHV) into science and art courses, with a focus on the perspectives of educators and learners. It was shown that the opinions of students and teachers on UHV issues are stronger, indicating that these areas should be necessary to be studied. Even though STEM education may lead to more skill sets, it does not foster interpersonal interactions, which may cause rifts in later life. The results showed how crucial UHV is for understanding human interactions and producing happiness. The dataset was grouped using EDM techniques.

The nature of the questionnaires, which assess or forecast whether or not UHV should be implemented as well as how and to what degree it should be implemented, leads to the conclusion regarding the data's significance. On the other hand, the analytical graphs and charts determine whether or not value based education or UHV should be implemented.

Using clustering algorithms and questionnaires, it has been determined and assessed that the UHV-STEM / UHV-STEAM / VbSTEM / VbSTEAM educational model ought to be put into practice in order to promote a contented, wealthy, prosperous, healthy, happy, fearlessness, and peaceful society. By evaluating items such as comparison outcomes, impact assessments for students' holistic development and self-assessment batteries based on UHV content exploration among students and teachers, future research may be able to predict students' behavior, and further using deep learning, artificial intelligence, more precise model can be developed.

**Funding:** No funding was provided for the completion of this study.

## DECLARATIONS

**Conflict of Interest:** The researcher declares that they have no conflict of interest.

## REFERENCES

Agrawal, R., Imieliński, T., & Swami, A. (1993, June). Mining association rules between sets of items in large databases. In Proceedings of the 1993 ACM SIGMOD international conference on Management of data (pp. 207-216).

Ankerst, M., Breunig, M. M., Kriegel, H. P., & Sander, J. (1999). OPTICS: Ordering points to identify the clustering structure. ACM Sigmod record, 28(2), 49-60.

Antonenko, P. D., Toy, S., & Niederhauser, D. S. (2012). Using cluster analysis for data mining in educational technology research. Educational Technology Research and Development, 60, 383-398.

Asif, R., Merceron, A., Ali, S. A., & Haider, N. G. (2017). Analyzing undergraduate students' performance using educational data mining. Computers & education, 113, 177-194.

Armstrong, R. L. (1987). The midpoint on a five-point Likert-type scale. Perceptual and motor skills, 64(2), 359-362.

Babu, G., & Satya, S. (2024). Understanding the Inherent Interconnectedness and other Salient Characteristics of Nature crucial for Sustainability. Environment, Development and Sustainability, 26(1), 2493-2505.

Babu, G., Satya, H., Satya, S., & Pandey, B. N. (2024). Looking at Sustainability More Fundamentally: Quest for a Holistic Worldview. Journal of Human Values, 09716858241258030.

Baker, R. S., & Yacef, K. (2009). The state of educational data mining in 2009: A review and future visions. Journal of educational data mining, 1(1), 3-17.

Bansal, A., Panchal, T., Jabeen, F., Mangla, S. K., & Singh, G. (2023). A study of human resource digital transformation (HRDT): A phenomenon of innovation capability led by digital and individual factors. Journal of Business Research, 157, 113611.

Barr, T., & Luo, T. (2025). HyFlex course design: outcomes, challenges, and supports for students and instructors. Journal of Computing in Higher Education, 1-29.

Basha, S. J., Rao, A. K., & Ammannamma, T. (2025). Transforming Education With Predictive Analytics: A Data-Driven Approach to Student Achievement. In Driving Quality Education Through AI and Data Science (pp. 433-456). IGI Global Scientific Publishing.

Batool, S., Rashid, J., Nisar, M. W., Kim, J., Kwon, H. Y., & Hussain, A. (2023).

Educational data mining to predict students' academic performance: A survey study. Education and Information Technologies, 28(1), 905-971.

Cetto, A. M., Schneegans, S., & Moore, H. (2000). World Conference on Science: Science for the Twenty-first Century; a New Commitment, Budapest. p. 29-32

Chakrabarti, S., Ester, M., Fayyad, U., Gehrke, J., Han, J., Morishita, S., ... & Wang, W. (2006). Data mining curriculum: A proposal (Version 1.0). Intensive working group of ACM SIGKDD curriculum committee, 140, 1-10.

Choi, Y., Lim, Y., & Son, D. (2017). A semantic network analysis on the recognition of STEAM by middle school students in South Korea. EURASIA Journal of Mathematics, Science and Technology Education, 13(10), 6457-6469.

Crisp, G., Nora, A., & Taggart, A. (2009). Student characteristics, pre-college, college, and environmental factors as predictors of majoring in and earning a STEM degree: An analysis of students attending a Hispanic serving institution. 924-942.

DAS, P., KOVURI, K., & SAHA, S. (2025). SCALABILITY AND EFFICIENCY OF CLUSTERING ALGORITHMS FOR LARGE-SCALE IoT DATA: A COMPARATIVE ANALYSIS. Journal of Theoretical and Applied Information Technology, 103(10).

Díaz, B., Lynch, C., Delgado, C., & Han, K. (2025). Analysis of two pedagogical approaches to foster discipline integrations in an educational data mining class using communities of practice. International Journal of STEM Education, 12(1), 17.

Durachman, Y., & Rahman, A. W. B. A. (2025). Clustering Student Behavioral Patterns: A Data Mining Approach Using K-Means for Analyzing Study Hours, Attendance, and Tutoring Sessions in Educational Achievement. Artificial Intelligence in Learning, 1(1), 35-53.

Durairaj, M., & Vijitha, C. (2014). Educational data mining for prediction of student performance using clustering algorithms. International Journal of Computer Science and Information Technologies, 5(4), 5987-5991.

Feldman-Maggor, Y., Barhoom, S., Blonder, R., & Tuvi-Arad, I. (2021). Behind the scenes of educational data mining. Education and Information Technologies, 26(2), 1455-1470.

Gasiewski, J. A., Eagan, M. K., Garcia, G. A., Hurtado, S., & Chang, M. J. (2012). From gatekeeping to engagement: A multicontextual, mixed method study of student academic engagement in introductory STEM courses. Research in higher education, 53, 229-261.

Gaur, R.R.,Sangal, R., & Bagaria, G.P.(2010). A Foundation course in Human Values and Professional Ethics. 2010, Excel Books Private Limited.

Hamdipour, A., Basiri, A., Zaare, M., & Mirjalili, S. (2025). Artificial rabbits optimization algorithm with automatically DBSCAN clustering algorithm to similarity agent update for features selection problems. The Journal of Supercomputing, 81(1), 150.

Hongell, P. (2025). Data and Analytic Maturity: A Framework for Data-driven Decision Making and Leadership.

Issah, I., Appiah, O., Appiahene, P., & Inusah, F. (2023). A systematic review of the literature on machine learning application of determining the attributes influencing academic performance. Decision Analytics Journal, 100204.

Kalita, E., Oyelere, S. S., Gaftandzhieva, S., Rajesh, K. N., Jagatheesaperumal, S. K., Mohamed, A., ... & Ali, T. (2025). Educational data mining: a 10-year review. Discover Computing, 28(1), 1-25.

Kerimbayev, N., Adamova, K., Shadiev, R., & Altinay, Z. (2025). Intelligent educational

technologies in individual learning: a systematic literature review. Smart Learning Environments, 12(1), 1.

Kiyani, M. N. (2025). A Framework to Design Transformative and Transdisciplinary Student-Led STE (A) M Clubs to Develop Students' Sustainability Competencies. In North American and European Perspectives on Sustainability in Higher Education (pp. 667-680). Cham: Springer Nature Switzerland.

Kord, A., Aboelfetouh, A., & Shohieb, S. M. (2025). Academic course planning recommendation and students' performance prediction multi-modal based on educational data mining techniques. Journal of Computing in Higher Education, 1-39.

Khan, K., Rehman, S. U., Aziz, K., Fong, S., & Sarasvady, S. (2014, February). DBSCAN: Past, present and future. In The fifth international conference on the applications of digital information and web technologies (ICADIWT 2014) (pp. 232-238). IEEE.

Kukkar, A., Mohana, R., Sharma, A., & Nayyar, A. (2024). A novel methodology using RNN + LSTM + ML for predicting student's academic performance. Education and Information Technologies, 1-37.

Kurday, M., & Vladova, G. (2025). Learning analytics and educational data mining applications: bibliometric and ChatGPT-based analysis of research publications from 2014 to 2023. Journal of Computers in Education, 1-36.

Liao, C. (2016). From interdisciplinary to transdisciplinary: An arts-integrated approach to STEAM education. ART education, 69(6), 44-49.

Liu, J., Peng, P., Zhao, B., & Luo, L. (2022). Socioeconomic status and academic achievement in primary and secondary education: A meta-analytic review. Educational Psychology Review, 34(4), 2867-2896.

López-Meneses, E., Mellado-Moreno, P. C., Gallardo Herrerías, C., & Pelícano-Piris, N. (2025). Educational Data Mining and Predictive Modeling in the Age of Artificial Intelligence: An In-Depth Analysis of Research Dynamics. Computers, 14(2), 68.

Parhizkar, A., Tejeddin, G., & Khatibi, T. (2023). Student performance prediction using datamining classification algorithms: Evaluating generalizability of models from geographical aspect. Education and Information Technologies, 28(11), 14167-14185.

Peña-Ayala, A. (2014). Educational data mining: A survey and a data mining-based analysis of recent works. Expert systems with applications, 41(4), 1432-1462.

Peng, K., Leung, V. C., & Huang, Q. (2018). Clustering approach based on mini batch kmeans for intrusion detection system over big data. IEEE access, 6, 11897-11906.

Regueras, L. M., Verdú, M. J., De Castro, J. P., & Verdu, E. (2019). Clustering analysis for automatic certification of LMS strategies in a university virtual campus. IEEE Access, 7, 137680-137690.

Romero, C., & Ventura, S. (2007). Educational data mining: A survey from 1995 to 2005. Expert systems with applications, 33(1), 135-146.

Salem, M., & Shaalan, K. (2025). Unlocking the power of machine learning in E-learning: A comprehensive review of predictive models for student performance and engagement. Education and Information Technologies, 1-24.

Sangsawang, T., & Yang, L. (2025). Predicting Student Achievement Using Socioeconomic and School-Level Factors. Artificial Intelligence in Learning, 1(1), 20-34.

Sasirekha, K., & Baby, P. (2013). Agglomerative hierarchical clustering algorithm-International Journal of Scientific and Research Publications, 83(3), 83.

Shin, D., & Shim, J. (2021). A systematic review on data mining for mathematics and science education. International Journal of Science and Mathematics Education, 19(4), 639-659.

Shukla, P., & Patel, S. (2025). Implementation of Students' Performance Using Modified K- Means Algorithm over Decision Tree.

Singh, D.K., Kumar, N. (2024). Analyzing Students Performance through Holistic and

Sustainable education approach in STEM through Educational Data Mining. In Tripathi, Durgesh, Sharma, Ramesh Kumar, & Tandon Surabhi (Eds.) Foundations of Change Analysing the Impact of National Education Policy, 2020 on India's Educational Landscape (pp. 145-164). London, United Kingdom: HP HAMILTON LIMITED

Singh, D.K., Kumar, N. (2024). A Systematic Survey for Students Performance Prediction with Holistic and Sustainable Education approach using Educational Data Mining. Tuijin Jishu/Journal of Propulsion Technology, Vol. 45 No. 2(2024), 232-269.

Singh, D. K. ., & Kumar, N. (2025). Exploring The Integration Of Universal Human Values In Arts And Science Education: Perceptions, Predictive Analysis, And Pathways To Uhv-Stem Using Clustering. Metallurgical and Materials Engineering, 364–375.

Smeets, K., Rohaan, E., van Der Ven, S., & Bakx, A. (2025). The effects of special educational needs and socioeconomic status on teachers' and parents' judgements of pupils' cognitive abilities. British Journal of Educational Psychology, 95(2), 321-345.

Su, Y. S., & Wu, S. Y. (2021). Applying data mining techniques to explore user behaviors and watching video patterns in converged IT environments. *Journal of Ambient Intelligence and Humanized Computing*, 1-8.

Suciati, N., Fabroyir, H., &Pardede, E. (2023). Educational Data Mining Clustering Approach: Case Study of Undergraduate Student Thesis Topic. IEEE Access, 11, 130072-130088.

Teixeira, P. B., Rocha, H., & Martins, C. (2025). Challenges and potential in implementing STE (A) M in teachers' practices: a systematic review. International Journal of Mathematical Education in Science and Technology, 1-17.

Xia, X. (2020). Clustering Analysis of Interactive Learning Activities Based on Improved BIRCH Algorithm. arXiv preprint arXiv:2010.03821.

Wang, L., Zheng, K., Tao, X., & Han, X. (2018). Affinity propagation clustering algorithm based on large-scale data-set. International Journal of Computers and Applications, 40(3), 1-6.

Webber, K. L., Stich, A. E., Grandstaff, M., & Case, C. (2025). Benefits of work-related experiences and their impact on career competencies for STEM students. Journal for STEM Education Research, 8(1), 155-178.

Williams, K. C., & Williams, C. C. (2011). Five key ingredients for improving student motivation. Research in higher education journal, 12, 1.

Wong, B., Li, K. C., & Liu, M. (2025). Evaluation of STE (A) M Education: An Analysis of Research and Practices from 2014 to 2023. Journal of Educational Technology Development and Exchange (JETDE), 18(1), 68-84.

Wu, K. L., & Yang, M. S. (2007). Mean shift-based clustering. Pattern Recognition, 40(11), 3035-3052.

Wu, M., & Ouyang, F. (2025). Using an integrated probabilistic clustering approach to detect student engagement across asynchronous and synchronous online discussions. Journal of Computing in Higher Education, 37(1), 299-326.