MVC in machine learning: a decade of algorithmic advances, challenges, and applications–a systematic review

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ABSTRACT

This systematic review evaluates the developments in multi-view clustering (MVC), its challenges, and applications from 2009 to 2024 and synthesizes 157 studies selected according to preferred reporting items for systematic reviews and meta-analyses (PRISMA) 2020 guidelines. MVC overcomes the shortcomings of the traditional single-view approaches by using complementary information provided by heterogeneous data sources. We used a strict search strategy in the ACM Digital Library, IEEE Xplore, and Scopus, and then carefully examined the quality of the found articles. The significant results suggest that the MVC research has grown explosively, with China as the major contributor and IEEE/Elsevier as the leading publishers. Developments in algorithms include deep learning, graph-based models, and factorization. Ongoing issues include managing incomplete views, scalability, successful fusion strategies, and interpretability. The review points out the wide range of applications of MVC in various areas, including bioinformatics, social network analysis, and multimedia. Future research must create adaptive frameworks, improve the interpretability of models, and develop strong evaluation measures, thus unlocking the full potential of MVC in real-life data applications.

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1. INTRODUCTION

The spread of multi-view data has transformed data-driven applications by providing more detailed and complete representations of entities. Multi-view data occurs when multiple sources report the same objects. Examples are textual profiles, interaction graphs, and images in social networks, protein, metabolite, and gene expression data in bioinformatics, video, represented by audio and frame, and web pages, characterized by text and links, as shown in Figure 1. Conventional single-view clustering algorithms are frequently ineffective in such situations since they do not take advantage of the complementary property of multiple views or do so in a sub-optimal way. The multi-view clustering (MVC) addresses this issue by successfully combining information and using redundancies and complementarities across views to generate more robust, accurate, and insightful clustering results [1].

MVC is concerned with integrating heterogeneous data sources that single-view methods cannot effectively incorporate, thus offering a more comprehensive representation. It can use complementary signals across views to boost clustering accuracy and interpretability. MVC has been used in different areas [2]. Computer vision combines color, texture, and shape features to enhance object recognition [3]. It combines genomic, transcriptomic, and proteomic data in bioinformatics to identify disease subtypes. Likewise, social network analysis combines textual and structural information to gain in-depth insight into social processes

[4]. As the amount and the diversity of data grow, the contribution of MVC to the complete and accurate analysis will only increase.

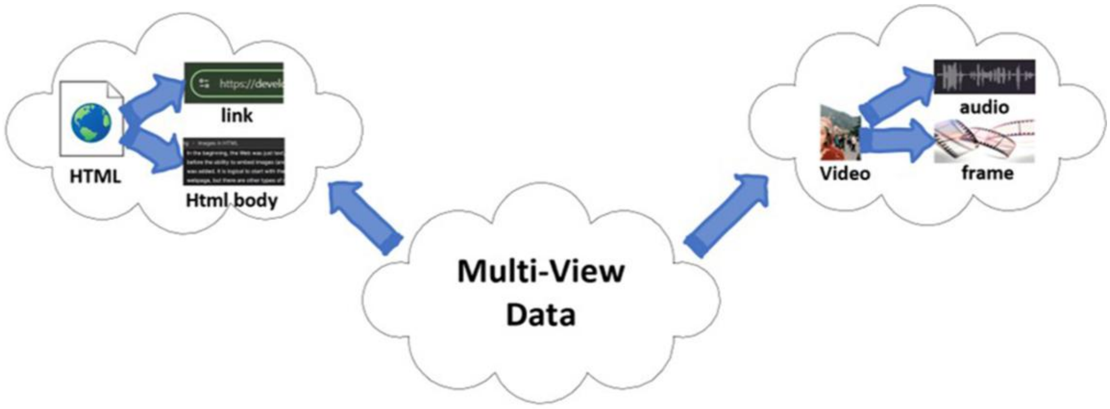

Figure 1. Illustrative examples of multi-view data (e.g., video and HTML web page)

MVC has significant challenges, even though it is promising. There are also issues of handling missing views, which are typical of real-world data, including in healthcare, where genetic or imaging data of patients may be unavailable [5]–[7]. View-specific noise can impair performance clustering, e.g., irrelevant text descriptors or poor-quality images, unless filtered [8]–[10]. It is also challenging to combine views effectively, since inefficient fusion mechanisms may overemphasize certain views and reduce the quality of clustering [11]–[13]. Moreover, scalability and heterogeneity are other issues, because MVC must be able to manage large and heterogeneous data effectively and accommodate heterogeneous distributions of features across views [12], [14], [15].

These limitations suggest that more powerful, accurate, and scalable MVC solutions are required. In particular, the issues of missing data [5]–[7], noisy or irrelevant features [8]–[10], effective view-integration strategies [11]–[13], and computationally efficient methods [14]–[16] are still crucial open research issues. There have been many efforts to address these problems in this dynamic field.

To explore these aspects systematically and to make a contribution to the current developments in MVC, the following research questions guide this review:

a. What are the key advancements in MVC algorithms over the past decade?
b. What are the primary challenges faced by MVC algorithms?
c. What are the applications of MVC in real-world scenarios, such as bioinformatics, social network analysis, and multimedia?

This systematic review aims to add to the body of knowledge and development of MVC techniques, which can manage the complexities of the real world, through a thorough analysis of existing methods, classifying them, the significant contributions, and future research directions.

2. METHOD

The research was based on a methodical literature review of MVC developments, challenges, and applications. To guarantee a rigorous and transparent methodology, this systematic review followed the preferred reporting items for systematic reviews and meta-analyses (PRISMA) 2020 guidelines [17].

2.1. Search strategy

The search strategy outlines selecting the most suitable primary studies (PS) indexed in several digital libraries. In this regard, the strategy narrowed down to papers published in peer-reviewed journals to achieve scientific rigor. This was carried out in two stages.

a. Phase 1. The initial step entailed identifying the keywords for the search protocol. This move was guided by several pre-searches that assisted in narrowing down and choosing the most suitable set of terms. Identifying specific and representative keywords was necessary, which directly affected the quality and relevance of the found studies. Table 1 shows the final keywords that were used in this SLR.

Table 1. Keywords used in the search strategy for MVC literature

A	B
Multiview clustering	Algorithm
MVC	Application
	Bigdata processing
	Bioinformatics
	Challenge
	Challenges
	Cloud computing
	Multimedia
	MVC
	Social network analysis
	Systematic review

b. Phase 2. The identified keywords were then systematically used in the second stage in various digital libraries. In (1) formalized "Boolean combinations of these keywords to provide consistency and reproducibility. This methodological design allowed for extensive literature coverage, reinforcing the strength and validity of the systematic review's findings.

$$Boolean\ expression\ of\ keywords = \left[(V_{i=1}^{2} A_i) \land \left(V_{j=1}^{11} B_j\right)\right] \tag{1}$$

2.2. Data sources

Choosing the right digital libraries is a decisive move in systematic reviews. Although other authors suggest a wide variety of databases, initial searches in this study showed that the results were highly overlapping. To minimize redundancy and stay focused, we limited the search to three well-known sources, so efficiency was not sacrificed at the expense of thorough coverage. ACM Digital Library, IEEE Xplore, and Scopus of Elsevier. The Mendeley tool was used to facilitate reference management, and Microsoft Excel was used to organize and track extracted data. An R package and Shiny app were used to generate a PRISMA flow diagram [18].

After the digital libraries and keywords were completed, the search expressions were formalized using (1) and implemented in each database. The main fields of inquiry were title, abstract, and keyword metadata formalized in (2). The queries that were run on each database are given in Table 2.

$$Boolean\ expression\ for\ the\ metadata\ of\ a\ paper = Title(E_1) \land Abstract(E_1) \land Keyword(E_1) \tag{2}$$

Table 2. Search queries executed across digital libraries

Database	Search query
ACM Digital Library	[[[All: "multi-view clustering"] OR [All: "multiview clustering"] OR [All: "multi-modal clustering"] OR [All: "co-clustering"]] AND [[All: "systematic review"] OR [All: algorithm]]] OR [[[All: "multi-view clustering"] OR [All: "multiview clustering"] OR [All: "multi-modal clustering"] OR [All: "co-clustering"]] AND [[All: challenge?] OR [All: application]]] OR [[[All: "multi-view clustering"] OR [All: "multiview clustering"] OR [All: "multi-modal clustering"] OR [All: "co-clustering"]] AND [[All: bioinformatics] OR [All: "social network analysis"] OR [All: multimedia] OR [All: "bigdata processing"] OR [All: "cloud computing"]]] AND [E-Publication Date: (01/01/2014 TO 31/12/2024)]
IEEE Xplore	((("Multi-view Clustering" OR "Multiview Clustering") AND ("Systematic Review" OR Algorithm)) OR (("Multi-view Clustering" OR "Multiview Clustering") AND (Challenge? OR Application)) OR (("Multi-view Clustering" OR "Multiview Clustering") AND (Bioinformatics OR "Social Network Analysis" OR Multimedia OR "Bigdata Processing" OR "Cloud Computing")))
Elsevier Scopus	TITLE-ABS-KEY(((("Multi-view Clustering" OR "Multiview Clustering") AND ("Systematic Review" OR algorithm)) OR (("Multi-view Clustering" OR "Multiview Clustering") AND (challenge? OR application)) OR (("Multi-view Clustering" OR "Multiview Clustering") AND (bioinformatics OR "Social Network Analysis" OR multimedia OR "Bigdata Processing" OR "Cloud Computing")))) AND PUBYEAR > 2008 AND PUBYEAR < 2025 AND (LIMIT-TO(SUBJAREA, "COMP")) AND (EXCLUDE(DOCTYPE, "le") OR EXCLUDE(DOCTYPE, "cr") OR EXCLUDE(DOCTYPE, "sh")) AND (EXCLUDE(LANGUAGE, "Chinese"))

Search filters were used on the digital libraries to refine the results further. For example, publication year was limited to 2014-2024 in both ACM Digital Library and IEEE Xplore, but the search in Scopus was set to a more recent start date to cover the entire review period, 2009-2024.

2.3. Selection process, exclusion and inclusion criteria, and quality assurance

To be rigorous and transparent, the selection process was based on PRISMA [17] guidelines as shown in Figure 2. The initial search in the three databases chosen retrieved 1,793 records. After eliminating 340 duplicates, 1,453 unique records were retained for initial screening.

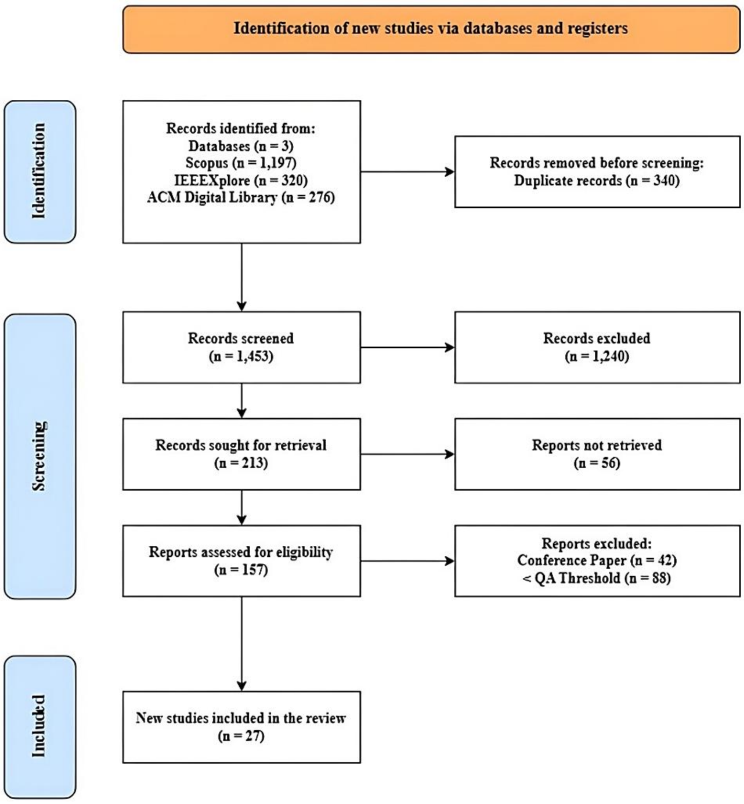

Figure 2. PRISMA flow diagram for literature identification, screening, eligibility, and inclusion

Titles and abstracts that included MVC, multiview clustering, or variations of these terms were included at this stage, resulting in 628 records. Abstract screening reduced the list to 213 studies. Of these, 56 records were eliminated because of problems, such as inaccessibility or incomplete records. Out of the 157 records (which formed the basis for our descriptive analysis), we filtered out conference papers, which aligned with our interests in peer-reviewed journal articles, resulting in a shortlist of 115 articles to review in full-text. These papers were then reviewed in full-text to ensure they were relevant to the research objectives and dealt with algorithmic developments, current challenges, or practical uses of MVC.

2.4. Quality assessment

A list of quality criteria (QC) was established to ensure reliability and reduce bias, as shown in Table 3. A rubric was used to score each study with a maximum of 25 points, and only those who scored above a threshold score of 22 were included in the core analysis.

Table 3. Quality assessment criteria for selected studies

Criteria	Description	Score range
Novelty	Does the study introduce new concepts or methods?	1-5
Methodological rigor	Are the methods sound, reproducible, and well-documented?	1-5
Citation impact	How influential is the paper in the field?	1-5
Relevance to topic	How closely does the study align with the review’s focus?	1-5
Clarity and structure	Is the paper well-written and logically organized?	1-5

3. RESULTS

This section presents the findings of the systematic literature review through a comprehensive descriptive analysis, followed by an in-depth discussion addressing the research questions. The trends of the publication in MVC research, as illustrated in Figure 3, can be described as having three different stages, namely: an initial phase of low output, a growth phase where the number of publications increased steadily, and an expansion phase where the number of publications increased at a high rate of 254%. This trend has continued into 2024, highlighting the long-term and high interest in MVC as a practical methodology in the data science field. This spurt of publications indicates the growing prevalence of multi-view data and highlights the natural constraints of single-view methods to provide a comprehensive understanding [19].

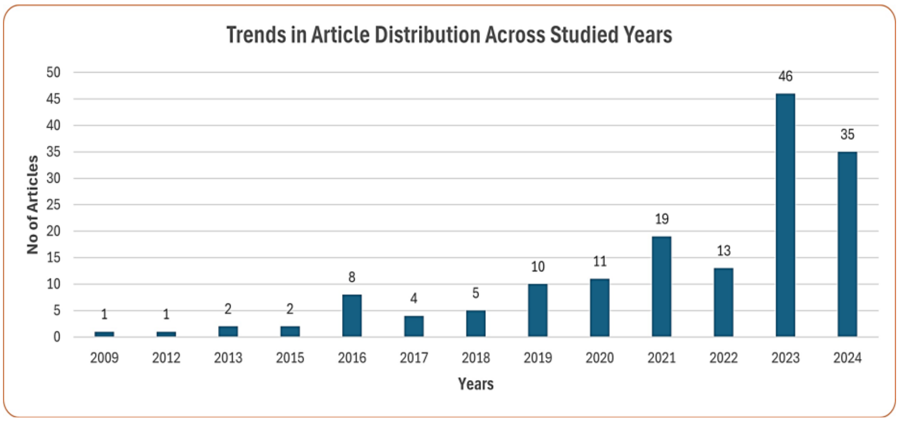

Figure 3. Publication trends in MVC research (2009–2024)

Figure 4 shows the distribution of publishers of the identified MVC research, where the most notable source is the Institute of Electrical and Electronics Engineers Inc., with 52 articles out of 154. Elsevier was next with 47 articles; IEEE Computer Society and AAAI Press were also significant contributors, followed by Springer and ACM. Most other publishers were poorly represented and had one or two publications each. Such a focus shows that MVC is primarily published in IEEE and Elsevier. This demonstrates their high popularity as a source of AI and machine learning publications, especially in this direction. The spread among the publishers indicates that MVC research aligns well with mainstream electrical engineering and computer science conferences.

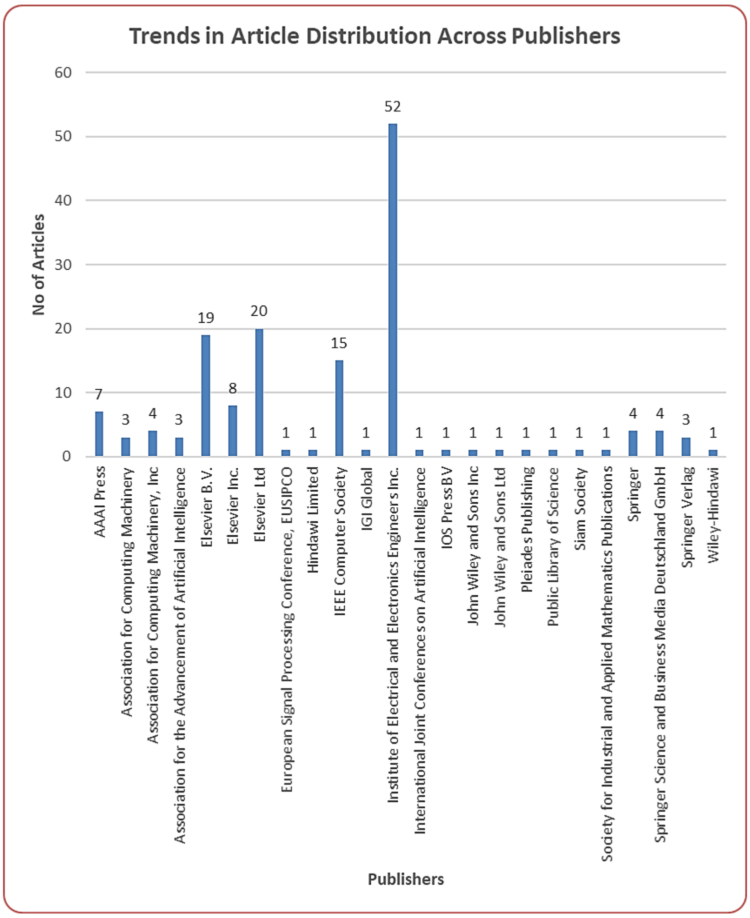

Figure 4. Distribution of MVC publications across publishers

China shows strong leadership in MVC research and has contributed to 91% (143 of 157) of the total number of articles that concentrate on developing MVC methodology, as shown in Figure 5. Other countries like India, the United States, and Malaysia also have fewer contributors to articles, with Germany, Greece, Japan, Singapore, and Algeria each contributing one publication. The statistics show an intense concentration of the research output of China, which implies a great academic and industrial interest in MVC. However, the input of other nations is relatively low. This spatial concentration brings out specific regional research priorities and the allocation of resources to this area of specialization.

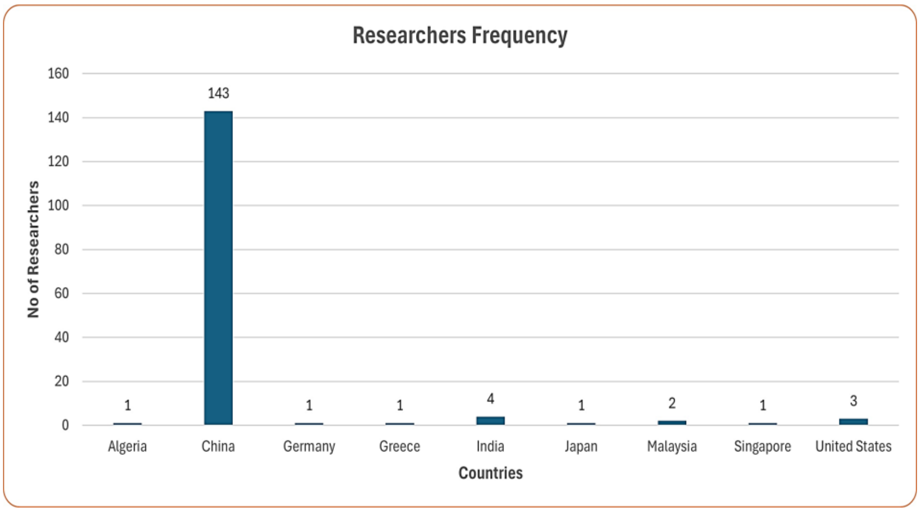

Figure 5. Geographical distribution of MVC research contributions

Figure 6 shows that MVC research is mainly published in journals, indicating the preference for extensive studies that undergo thorough peer review. Conversely, conference papers emphasize the latest trends and discoveries at academic and industry conferences. This distribution indicates that although conference talks can help develop MVC research, journals are the primary source of thorough theoretical research and massive studies. This trend highlights the focus of the academic community on fully validated and mature research to be distributed in the MVC field.

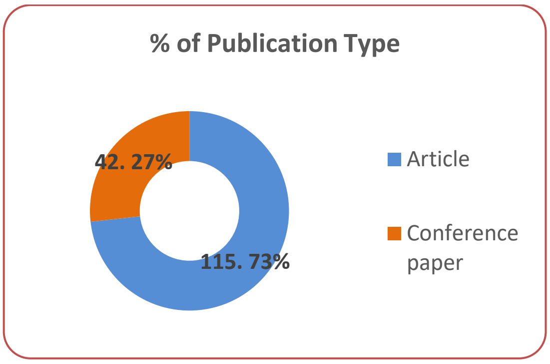

Figure 6. Distribution of MVC publications by type

The analysis of the MVC research citation patterns shows a significant difference in the influence, as shown in Figure 7. Although most publications are moderately academically treated, a substantial proportion are not referenced. A few studies have been highly cited, such as one that has received 839 citations, which are foundational contributions and have a significant impact in the field. This dispersion indicates that the MVC research domain is immature, and a few seminal works are widely cited that determine the future direction of the research area, even though the contribution of most other studies is limited. The trend suggests that more visibility and access to emerging research are required to enhance wider involvement and speed up the development of MVC.

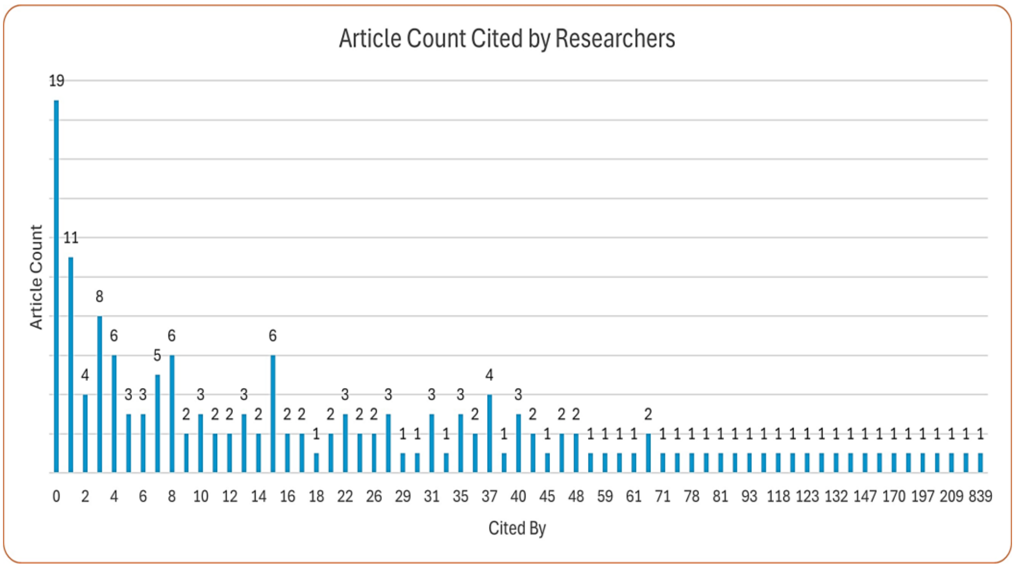

Figure 7. Citation distribution patterns of MVC articles

Figure 8 outlines the datasets commonly used to benchmark MVC algorithms. These are such prominent ones as Handwritten [20], [21], 3Sources [5], [20], BBCSport [20]–[22], and ORL [5], [23], [24], and MSRC-v1 [20], [21], Reuters [5], [22], BBC [5], [20], and Coil20 [25], which are widely used in different MVC applications. Moreover, a smaller group of datasets is presented in only six studies, meaning they are used less but are still present. The fact that Text, Image, and Multimodal datasets are the most common implies that they can be used in a wide range of real-world uses of MVC. These multi-view datasets allow for a thorough assessment of algorithms that aim to utilize specific feature spaces to achieve better clustering results [25].

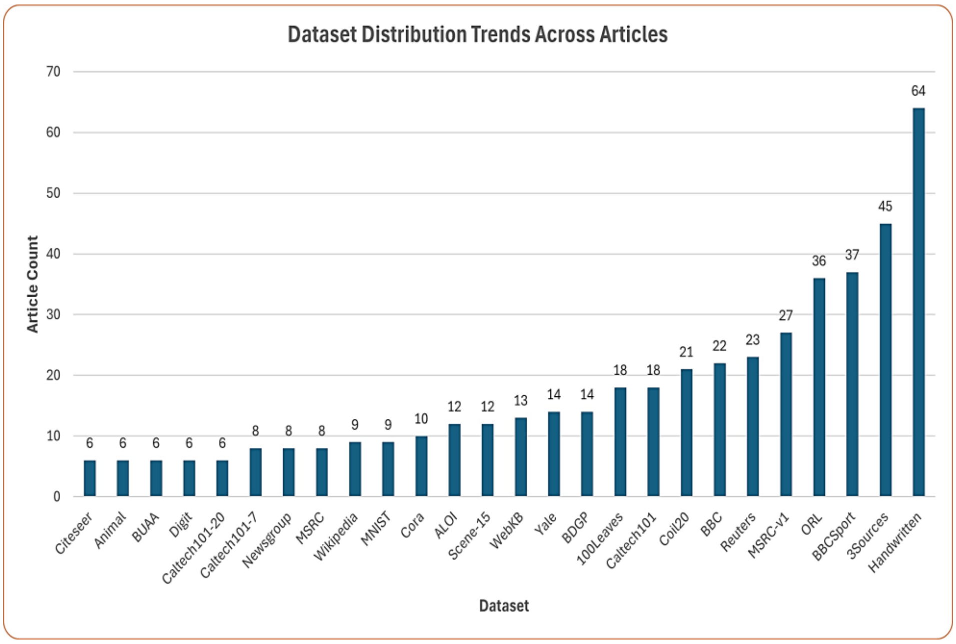

Figure 8. Frequently used datasets for MVC research

The detailed findings are provided in the subsections below, and each research question that informed this systematic review is addressed.

Research question 1: what are the key advancements in multi-view clustering algorithms over the past decade?

In the past decade, there has been a surge in MVC, especially graph-based [26], spectral clustering-based [4], and subspace clustering-based algorithms [27], as well as non-negative matrix factorization-based methods [14], [28]–[30]. The goal of these methodologies is to combine effectively the heterogeneous information of multiple perspectives to generate more robust and accurate data partitions [31].

To give a holistic picture of these developments, Table 4 (in Appendix) [2]–[4], [10], [11], [21], [30], [32]–[47] summarizes the primary MVC methods, their strengths, weaknesses, and where they are typically applied. This comparative study helps to comprehend the changing nature of MVC algorithms and their applicability to various real-life issues.

In particular, more recent developments in spectral clustering have aimed at creating more coherent graph constructions that reflect the relationship within the individual data views and across different data views in a more effective manner [2], [48], [49]. Likewise, subspace approaches are also placing more focus on learning a shared, low-dimensional representation that maintains the underlying data structure across views [7], [39], [50]. There has also been significant development of the co-training-based models that seek to maximize mutual agreement between multiple views [1], [38], [51]–[53]. These methods utilize the complementary information of multi-view data and produce stronger and more precise clustering results than single-view methods [54].

Deep learning has led to the creation of neural network-based MVC [6], [21], [34], [38], [44], [45], [47], [55], [56]. These methods use the multi-view data to learn more discriminative representations with the help of complex architectures [21], [38]. In many cases, deep learning methods use contrastive learning paradigms, in which models are trained to distinguish between similar and dissimilar data points, improving feature extraction and fusion across disparate views, resulting in higher clustering performance than traditional methods [46], [57]. Deep MVC algorithms (where learned representations are less distinct or informative), specifically have demonstrated potential in non-linear, high-dimensional data by leveraging deep neural networks to extract holistic, complementary and multi-level features, addressing the weaknesses of the traditional algorithms that may miss cross-view differences in data or rely on single-lane neural networks [21], [38], [45]. These approaches tend to build a composite similarity matrix or a consensus representation for spectral clustering or k-means, respectively, by combining both consistent and complementary information across views [2], [8], [10], [58]–[60].

Nevertheless, there is a trade-off in the selection of the method. Although the methods based on matrix factorization are highly computationally efficient, they might fail to represent non-linear data structures sufficiently [36]. Conversely, though strong in modeling complex nonlinear relationships, deep learning-based approaches can be associated with higher computational complexity and lower interpretability. Nevertheless, deep MVC methods are still being improved, with techniques that combine kernel learning and subspace methods potentially demonstrating improved applicability to various complex data. As an example, graph-based MVC algorithms tend to integrate information on intrinsic features of multiple views into a spectral embedding space, resulting in better performance [10], [54].

Research question 2: what are the primary challenges faced by multi-view clustering algorithms?

MVC algorithms leverage the complementary nature of multiple data representations to uncover latent structures more effectively than single-view approaches. However, this potential is constrained by persistent challenges affecting data quality, algorithmic design, scalability, and theoretical rigor.

a. Data quality and view incompleteness

The problem of incomplete multi-view data, in which cases complete views are not available, causes a significant loss of information and prevents the overall perception of underlying patterns [58], [61], [62]. This is especially acute in practical datasets. In this case, the failure of data acquisition or privacy issues may cause the absence of individual samples in some views altogether, which makes the traditional imputation techniques less efficient [23], [63]. This issue is called incomplete MVC and requires strong algorithms that efficiently deal with partial information. These algorithms should not only be able to preserve clustering performance, but also not introduce spurious correlations [64]. Other approaches, such as imputing missing samples in the clustering process itself, help to reduce the harmful impact of missing data, which is essential since applying traditional methods to such data directly usually produces suboptimal results by ignoring natural structural information [65]. Alternatively, methods such as those based on matrix factorization or kernel learning can adapt to incomplete views by either reconstructing the missing data or by learning a consensus representation across available views [58]. Despite these adaptive mechanisms, conventional matrix completion algorithms tend to be ineffective at filling these missing values, notably when complete rows or columns are missing, thus restricting the usefulness of most existing MVC algorithms that assume complete datasets [5], [37], [66]–[69]. This highlights the need for strong algorithms to deal with incomplete information effectively. Moreover, the different quality and reliability of various views is another serious problem, which can worsen the performance of overall clustering when not properly weighted or filtered

[35], [46], [70]. In particular, missing data, either because of inaccessibility or because of accidental incompleteness, often leads to incomplete multi-view datasets, as is the case with various medical tests, with some patients not having specific test results [5]. In these cases, conventional MVC algorithms, which often assume full views, are mostly ineffective [58], [66].

The quality of data, especially the noise and incompleteness of views, directly affects the success of fusion strategies, since these mechanisms have difficulties in balancing conflicting signals and, therefore, assigning clusters unsteadily. As a result, the solution of these data quality problems may also impact scalability since more complex imputation or alignment methods are required, raising the computation cost. These issues may necessitate sophisticated methods, including powerful subspace learning or adaptive graph building, which necessarily involve more computational resources and algorithm complexity [5].

b. Algorithmic limitations and fusion strategies

The main challenge is successfully combining information across multiple perspectives because simple concatenation can fail to reflect the underlying relationships, and may also add harmful noise [71]. This difficulty is magnified when trying to optimally weigh the contribution of each view, especially in cases where views have different degrees of reliability or relevance, which requires adaptive weighting schemes [10], [12], [43], [72]. A second common problem is the correct correspondence of features between views, particularly when heterogeneous data types are involved, or when feature spaces differ, which may distort object similarities and undermine clustering integrity [25]. Therefore, formulating effective fusion strategies that consider view heterogeneity and different data quality is still a research-intensive issue, especially in cases where some views might include redundant or irrelevant data, which can bias the clustering process [69], [73]. Numerous methods aim to resolve this by inferring missing data, but this may add bias or noise, particularly when the gaps between data are significant [69], [73]. This requires advanced imputation models using inter-view correlations to fill in missing entries, not deterministic replacements predictively.

c. Scalability and computational burden

The computational complexity of many multi-view algorithms is frequently non-linear with the number of views, dimensions, and samples, making many more complex multi-view algorithms infeasible on large datasets [20], [21], [74]. This is limited by the requirement to build large similarity matrices or tensors and to optimize complexly, which requires a lot of memory and processing power, especially in graph-based or kernel-based methods [20], [21], [75], [76]. Moreover, the iterative optimization steps used by most deep MVC algorithms add further computational complexity [20], [21], [77], and thus implementing them on resource-limited systems is difficult. This problem is often compounded by the deep learning architecture integrations, which, although they offer the benefits of extracting complex multi-view representations, come at the cost of long training times and large memory footprints of neural networks [77]. This requires more effective algorithms and distributed computing paradigms to support the growing volumes of data experienced in modern applications [20], [21].

Research question 3: what are the applications of multi-view clustering in real-world scenarios, such as bioinformatics, social network analysis, and multimedia?

MVC has been widely used in many fields, with the advantage of combining the complementary information of multiple data perspectives to increase the accuracy and strength of the analysis [25]. This encompasses its use in bioinformatics to analyze multi-omics data [20], [21], [78], in social network analysis to understand complex user interactions [20], [21], and in multimedia to organize and retrieve content by combining visual, audio, and textual information [20], [21], [79]. An example is in medical diagnostics, where MVC is used to determine disease subtypes, combining clinical history, genomic profiles, and radiographic information, which can help more accurately stratify patients and develop more personalized treatment plans [20], [21], [80], [81]. Likewise, MVC can be used in cybersecurity to detect abnormal network behavior by synthesizing packet metadata, system logs, and user activity records. This goes a long way in helping to detect advanced cyber threats that single-view detection techniques would otherwise miss because of the holistic nature of disparate data streams. In addition to cybersecurity, MVC can be used to integrate satellite images, spectral data (e.g., data at various light wavelengths), and geographical data to enhance land cover classification and environmental monitoring in other areas, such as remote sensing [20], [21]. In recommender systems, such as MVC, user preferences, item attributes, and social ties are analyzed to produce more precise and varied recommendations, overcoming the constraints of content-based or collaborative filtering. Likewise, MVC integration is also invaluable in materials science to classify complex material structures by integrating atomic-level simulations, experimental measurements, and crystallographic data, and thus discover new materials with desired properties [82]. These applications emphasize the importance of MVC in gaining richer information about heterogeneous data, and that it can offer a more complete picture than single-view analyses [20], [21], [83].

4. CONCLUSION

MVC has experienced much development in the past decade, with many methodological advances. Although deep learning models have enhanced the extraction of high-level, non-linear representations, and graph-based models have performed well in modelling the inter-view structural relationships. Their interpretability and strength of latent representations remain in matrix and tensor factorization, and subspace learning is appropriate to align noisy or heterogeneous views. Ensemble strategies provide clustering stability in various ways, whereas probabilistic and Bayesian methods give flexibility and modelling of the uncertainties in realistic situations. With these developments, however, essential concerns still require more focus on MVC methods to be practical and reliable. It is worth noting that algorithms that can directly model and learn incomplete multi-view data are needed, because existing methods usually bias the results or miss important information. Moreover, the heterogeneity of multi-view data, where different distributions, dimensionalities, noise levels, and data types may occur, is a significant integration challenge. Correspondingly, existing integration techniques do not necessarily capture complex intra-view semantics and inter-view correlations, and more sophisticated mechanisms are needed. Scalability and computational efficiency are still significant challenges of large-scale, real-time environments, especially graph-based or deep learning MVC models, which highlights the importance of more efficient algorithms. Decoupling representation learning and clustering in most frameworks may result in sub-optimal performance; thus, additional investigation of joint learning frameworks is warranted. Most MVC models, particularly black-box deep learning models, should be made more interpretable and transparent, because interpretable models are essential in high-stakes domains. In addition, the absence of uniform evaluation procedures makes it difficult to compare and evaluate generalizability, and standardized benchmarking procedures are required. Finally, distributed MVC is immature, and the existing literature is insufficient to cover the real-world limitations, meaning that there is a high demand for sound distributed MVC systems. These long-standing issues are the most critical to address to realize the full potential of multi-view learning and apply it transformatively in an ever more complex and data-rich world.

5. FUTURE WORK

In the last ten years, this survey has carefully explored the significant algorithmic developments, ongoing problems, and various practical uses of MVC. It has emphasized the importance of using multiple perspectives to obtain stronger and more informative solutions to clustering, especially in complicated datasets that single-view methods cannot address. This general summary highlights the urgent need for further research to solve the existing limitations and realize the potential of MVC in new areas of data-intensive data. Based on these insights, the following specific research questions are suggested for further work: i) adaptive frameworks and incomplete data handling ((i) how can adaptive MVC frameworks be designed to dynamically weigh view contributions based on their quality, relevance, and presence, thereby optimizing clustering performance across diverse data conditions? and (ii) what novel algorithmic approaches can effectively handle incomplete multi-view data by minimizing reliance on imputation and preserving inherent data structures?); ii) streaming multi-view data: ((i) what online or incremental learning techniques are most effective for robustly clustering streaming multi-view data in real-time scenarios?); iii) transfer and meta-learning integration ((i) how can transfer learning and meta-learning, including few-shot learning adaptations, be effectively integrated into MVC paradigms to enable more efficient adaptation to new datasets and tasks?); iv) model interpretability ((i) what methodologies can enhance the interpretability of MVC models, particularly for complex deep learning approaches, to provide transparent insights into view contributions and clustering decisions?); v) robust evaluation metrics ((i) what robust evaluation metrics can be developed or adapted to accurately assess and compare MVC algorithms, considering the unique challenges of multi-source data?); and vi) theoretical foundations ((i) what are the fundamental theoretical principles governing effective multi-view data fusion that can inform the design of more principled and robust MVC algorithms?). Addressing these research gaps will undoubtedly boost MVC into new frontiers, enabling its application in increasingly complex and dynamic real-world problems.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Rashmi Agarwal	✓			✓						✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The supporting data of this study are openly available in the GitHub Repository [mvcml-slr] at https://github.com/mvresearch/mvcml-slr.git.

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APPENDIX

Table 4. Comparative analysis of key MVC approaches

Approach	Pros	Cons	Typical use cases
Graph-based MVC	- Remarkable proficiency in capturing local nonlinear structures of data points and consistently achieving high clustering performance [32]. - Can learn an affinity graph for objects based on topological structure analysis [3].	- Rely heavily on fixed input graphs for clustering decisions [33]. - May not fully consider the importance of different views [10]. - Can fail to capture potential correlations between objects [3]. - Challenges with weight hyperparameters for individual views [33]. - Heavy computation limits applicability to large-scale data [34].	- Data where geometric structural information is essential, e.g., image categorization, motion segmentation, group detection in computer vision [2]. - Document categorization in natural language processing, where text documents have multiple language representations [2]. - Gene detection for complex diseases [2].
Spectral clustering-based MVC	- Promising clustering performance and well-defined mathematical framework [11]. - Can be robust to data sparsity [4]. - Effective in integrating multiple information by co-regularizing clustering hypotheses [35].	- Optimization is an NP-hard problem (meaning it's computationally challenging to solve exactly for significant inputs) due to discrete constraints on clustering labels [11]. - Often require post-processing, which can introduce uncertainty [36]. - Computationally expensive for large-scale data (O(N^3)) complexity for eigenvalue decomposition) [36]. - Not good at clustering high-dimensional multi-view data without proper similarity graph construction. - May not fully consider the importance of different views [10]. - Can perform poorly on incomplete views if assumptions are violated [4].	- Learning a common intrinsic subspace for various views in image processing [35]. - General multi-view data clustering using spectral graph theory [10].
Subspace clustering-based MVC	- Identify compatible features across views, improving clustering accuracy [3]. - Generally, there are fewer time and space complexities [37]. - Suitable for handling high-dimensional data [38]. - Can learn a unified, low-dimensional representation while preserving distribution information [38]. - Effective in revealing actual hidden structures from high-dimensional data [39].	- May only exploit features of objects, ignoring relations between objects [3]. - Can involve high computational complexity and low accuracy for very high-dimensional multi-perspective data [40].	- High-dimensional data with diverse features in areas like computer vision [39]. - When data consists of samples from a union of various lower-dimensional subspaces [39]. - Learning an explicit non-linear data mapping for subspace clustering [34].
Non-negative matrix factorization-based MVC	- High interpretability and simple implementation [40]. - Useful in many research areas such as information retrieval and pattern recognition [41]. - Achieves competitive performance in text and biological data clustering [41]. - Widely utilized for web document summarization, clustering, and recommendation in data mining [30]. - Competence to handle heterogeneous data [30].	- Solutions may not be unique [42]. - Standard orthogonal basis matrices may not be obtained for each view [42]. - Can be sensitive to data sparsity [4]. - May only capture view-level importance, ignoring feature-level relationships [43].	- Text clustering, web document summarization [30], biological data clustering [41]. - Image processing [44]. - Recommendations [30].
Deep learning-based MVC	- Powerful in capturing complex non-linear relationships. - Effectively and efficiently learn hierarchical information embedded in data [21]. - Can extract more discriminative representations [21]. - Promising for high-dimensional and non-linear data [45]. - Capable of learning explicit non-linear mappings of data [34].	- Increased computational complexity and reduced interpretability. - Challenges in dealing with conflicts between the learning standard and private view information [46]. - Potential for representation degeneration [46]. - Extensive training times and substantial memory footprints.	- Complex, high-dimensional, non-linear multi-view datasets. - Extracting hierarchical information from multi-view data [21]. - Image processing [47], computer vision tasks [2].

Table 4. Comparative analysis of key MVC approaches *(continued)*

Approach	Pros	Cons	Typical use cases
Multi-kernel learning	- Can solve linearly inseparable problems [38]. - Enhance data representation ability and improve clustering performance [38]. - Better handling of high-dimensional data by spatially partitioning kernel functions [38]. - Robust in capturing data distribution information [38].	- High computational complexity [38]. - Poor interpretability [38]. - Requires careful choice of kernel functions [38]. - Significant time and space overhead [38].	- When dealing with high-dimensional data where different views require distinct kernel functions [38]. - Situations where multiple kernel functions are combined to capture data distribution [38] better.

BIOGRAPHIES OF AUTHORS

Pankaj Kumar is a distinguished research scholar at Manav Rachna International Institute of Research and Studies (MRIIRS) with a strong foundation in Data Science and Artificial Intelligence, having graduated from the prestigious Indian School of Business (ISB), Hyderabad. Currently serving as an Associate Manager in Data Engineering at DXC Technology, Noida. He brings a wealth of experience to his role, backed by 18 years of expertise in software development. In his current capacity, he leads and shapes the data engineering team, ensuring alignment with business objectives. His role demands strategic leadership and technical acumen, as he collaborates with cross-functional teams to drive the successful implementation of extract, transform, load (ETL) processes and data pipelines in an azure environment. Under his guidance, a team of data engineers, analysts, and QA engineers works cohesively to achieve project goals, strengthening the organization's data infrastructure. As a research scholar under the mentorship of Dr. Rashmi Agrawal, he has completed his coursework and is now delving into his research interest in unsupervised machine learning. His work aims to uncover hidden patterns and insights from the vast data generated from multiple sources. He's commitment to research is evident in his proactive approach, spearheading R&D initiatives and contributing to the academic community through conference paper publications at top international conferences. His dedication to pushing the boundaries of data science underscores his passion for making significant advancements in the field. He can be contacted at email: pankajsr@msn.com.

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