Bol. Soc. Paran. Mat.
©SPM – E-ISSN-2175-1188
SPM: www.spm.uem.br/bspm

(3s.) **v. 2026 (44) 7** : 1–12.
ISSN-0037-8712
doi:10.5269/bspm.81396

Autoencoder Based Nonnegative Matrix Factorization with Collaborative Consensus for Incomplete Multiview Clustering

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ABSTRACT: Aim of multiview clustering (MVC) is to partition the data into clusters by exploiting complementary information from multiple views. Conventional MVC approaches generally assume that all views are fully observed; however, this assumption is often not true in real-world scenarios where data incompleteness is inevitable. The performance of conventional MVC models degrades by such missing views. This limitation of MVC methods has motivated the development of incomplete multiview clustering (IMVC) methods. Existing IMVC methods are although promising still face challenges like robust latent representation, cross-view consensus and structure preservation under high missing ratios. To overcome this limitation, a novel Autoencoder based Nonnegative Matrix Factorization with Collaborative Consensus for incomplete multiview clustering (IMVC-AENMF) framework is proposed. The proposed method integrates three key components: First, an autoencoder-like factorization strategy that imposes encoder–decoder consistency to enhance the stability of latent representations. Second, a collaborative consensus learning mechanism that aligns view-specific latent spaces with a shared consensus representation, enabling effective cross-view knowledge transfer despite incompleteness. Third, a graph Laplacian regularization term that preserves the intrinsic manifold structure and ensures cluster smoothness. The unified objective function is inherently nonconvex, and an efficient alternating optimization algorithm with multiplicative update rules is derived to guarantee convergence to a local optimum. Extensive experiments on five commonly used datasets and one real-world financial dataset demonstrate that our framework not only achieves superior clustering performance compared to state-of-the-art incomplete MVC methods but also exhibits strong robustness against varying missing rates, thereby providing a powerful solution for practical multiview learning applications.

Key Words: Incomplete data, multiview clustering (MVC), nonnegative matrix factorization, graph regularization.

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2020 *Mathematics Subject Classification:* 68T10, 62H30, 65K05.
Submitted January 17, 2026. Published April 11, 2026

Typeset by $\mathcal{B}^{S}\mathcal{P}_{\mathcal{M}}$ style.
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1. Introduction

In the fields of data mining and machine learning, multiview data have become increasingly prevalent due to the availability of heterogeneous information collected from different sources [1,2,6,5]. The aim of multiview learning is to effectively exploit both the consistent and complementary information present across multiple views of the same data. Among various multiview learning tasks, multiview clustering (MVC) has received significant attention. The aim of MVC is to partition unlabeled data obtained from different views by jointly leveraging diverse feature representations, ultimately yielding more meaningful and robust clustering results. However, the multiview setting introduces several practical challenges, including heterogeneous feature spaces, high-dimensional representations, noisy observations, and scalability constraints [34,15].

Over the past decade, numerous MVC methods have been proposed, ranging from spectral clustering approaches [32,4,31,20] and graph-based formulations [36,27,25] to subspace clustering [16] and nonnegative matrix factorization (NMF)-based techniques [9,8,26]. Among these, NMF has gained particular prominence due to its ability to learn interpretable low-dimensional representations. MultiNMF [14,18,21] is an NMF-based MVC method, which enforces consensus among view-specific factorization results to achieve coherent clustering assignments across views. Other classical MVC strategies rely on centroid-level or pairwise co-regularization [7], where clustering is performed independently on each view followed by alignment of the resulting cluster assignments.

Despite their strong performance, most MVC models implicitly assume that all views are fully observed for every instance. However, this assumption rarely holds in real-world environments. In practice, multiview data are often incomplete due to sensor failures in monitoring systems, missing modalities in multimedia applications, privacy-restricted attributes in healthcare, or inconsistent data collection procedures across platforms. Such missing views or instances can significantly degrade the performance of traditional MVC algorithms, which are heavily dependent on complete cross-view information [35,17,37]. This limitation has motivated the development of incomplete multiview clustering (IMVC) methods.

IMVC approaches can be broadly categorized into non-inference and inference-based methods. Non-inference methods [13,19,22] attempt to cluster the data directly without explicitly recovering the missing views, often by constructing robust similarity graphs or consensus representations using only the available observations. For example, Wen et al. [28] designed incomplete similarity graphs with zero-padding for missing entries prior to spectral embedding, while Liang et al. [11] utilized adaptive sample-level weights for effective multiview fusion. Wen et al. [29] further incorporated local graph preservation to enhance robustness against incompleteness.

Inference-based methods, on the other hand, aim to explicitly reconstruct missing views or latent representations before clustering. Early inference models such as PVC [10] and MIC [23] employ low-rank or sparse matrix factorization to impute the missing data but remain limited by their linear assumptions. More advanced method DAIMC [3], incorporate probabilistic modeling, graph regularization, or instance-level alignment to better capture nonlinear cross-view relationships. Tensor-based approaches like IMVTSC [30] further exploit high-order structural dependencies to improve the recovery of missing views.

Although representation learning using autoencoder, nonnegative matrix factorization, and graph regularization have each been studied in multiview clustering but their direct application to incomplete multiview settings remains limited. Existing IMVC are promising still face challenges in jointly ensuring robust latent representation learning, cross-view consensus construction, and structure preservation under high missing ratios. To address these limitations, this work introduces a novel **Autoencoder based Nonnegative Matrix Factorization with Collaborative Consensus for incomplete multiview clustering (IMVC-AENMF)** framework. In contrast to classical NMF-based IMVC, proposed framework incorporates an encoder–decoder consistency constraint, which stabilizes latent representations and enhances robustness to missing views. Existing methods align latent spaces using pairwise constraints, while IMVC-AENMF introduces a unified consensus representation that simultaneously integrates multiple view-specific latent spaces, enabling effective knowledge transfer even when some views are missing. Also, prior works apply graph regularization on each view, while the proposed framework applies it on the shared consensus, which synergistically combines cross-view alignment with manifold preservation. This will ensure smooth cluster boundaries. The main contributions of proposed framework are as follows:

1. First, an autoencoder-like factorization formulation imposes encoder-decoder consistency, enhancing the stability and semantic quality of view-specific latent representations.

2. Second, a collaborative consensus learning mechanism aligns heterogeneous view-specific latent variables with a shared consensus representation, enabling effective knowledge transfer across incomplete views.

3. Third, a graph Laplacian regularization term is integrated to preserve underlying manifold structures and maintain smoothness across clusters.

The unified objective is nonconvex; nonetheless, an efficient alternating optimization strategy with multiplicative update rules is derived, ensuring convergence to a local optimum. Extensive experiments on widely used benchmark datasets and one real-world financial dataset demonstrate that the proposed method consistently outperforms state-of-the-art IMVC approaches in terms of clustering accuracy, normalized mutual information, and adjusted rand index. Furthermore, the model exhibits strong robustness across varying missing ratios, establishing it as an effective and practical solution for real-world incomplete multiview learning applications. The presented paper is organized as follows: section II is devoted to proposed methodology. Section III describes the experimental results obtained. Finally, Section IV concludes this paper.

2. Methodology

This section presents the proposed *IMVC:Autoencoder-like Nonnegative Matrix Factorization with Collaborative Consensus* framework for incomplete multiview clustering. The methodology is organized into five major components: (i) problem formulation, (ii) autoencoder-like nonnegative matrix factorization, (iii) collaborative consensus learning, (iv) graph Laplacian regularization, and (v) optimization using alternating update rules. The framework is specifically designed to exploit complementary information from multiple incomplete views while ensuring robust latent representation learning. Proposed framework is shown in figure 1.

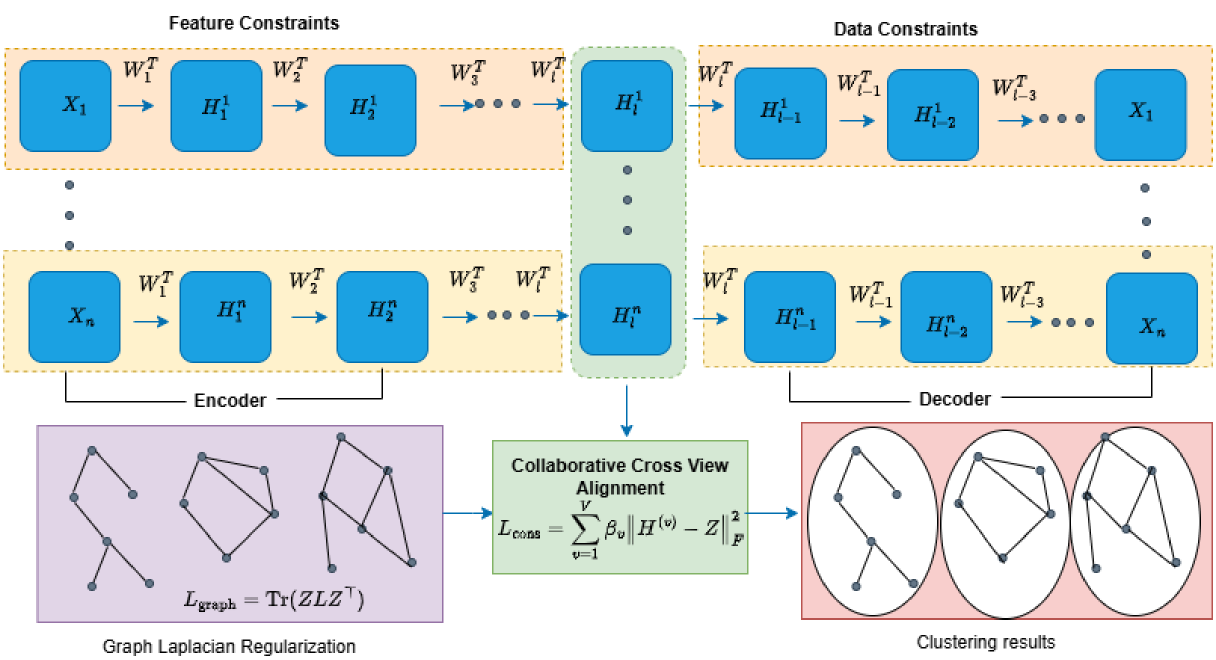

Figure 1: Proposed Framework

2.1. Problem Formulation

Let $\mathcal{X} = \{X^{(v)}\}_{v=1}^{V}$ denote a dataset represented by V heterogeneous views, where $X^{(v)} \in \mathbb{R}_{+}^{d_v \times n}$ contains n samples with d_v-dimensional features in view v. Due to real-world limitations, each view may be incomplete because of missing observations or unavailable modalities. Let $\Omega^{(v)} \in \{0,1\}^{d_v \times n}$ represent the observation mask such that:

$$X_{ij}^{(v)} \text{ is observed if } \Omega_{ij}^{(v)} = 1, \qquad X_{ij}^{(v)} \text{ is missing if } \Omega_{ij}^{(v)} = 0.$$

The goal of incomplete multiview clustering is to learn a unified representation $Z \in \mathbb{R}_{+}^{k \times n}$ that preserves complementary cross-view information and supports accurate clustering. The observation mask $\Omega^{(v)}$ ensures that only the available entries of each view contribute to the reconstruction loss. When a sample is missing in a view, it will not participate in the reconstruction term of that view. However, its latent representation will get updated through the collaborative consensus term that aligns $H^{(v)}$ with the shared representation Z. As a result, missing samples are implicitly inferred from other observed views by using the consensus space, rather than being discarded or filled with artificial values.

2.2. Autoencoder-like Nonnegative Matrix Factorization

For each view v, we employ an autoencoder-inspired NMF mechanism to enforce encoder-decoder consistency. The view-specific data matrix is factorized as:

$$X^{(v)} \approx W^{(v)} H^{(v)},$$

where $W^{(v)} \in \mathbb{R}_{+}^{d_v \times k}$ is a basis (decoder) matrix and $H^{(v)} \in \mathbb{R}_{+}^{k \times n}$ is the latent representation (encoder) of view v. In incomplete multiview settings, classical NMF reconstruction term relies only on the sparsely observed entries of $X^{(v)}$, which can lead to unstable latent representations. By requiring the latent variable $H^{(v)}$ to be predictable from a nonlinear encoding of the observed data, the model restricts the solution space and prevents unstable factorizations.

$$H^{(v)} \approx \phi\big(W^{(v)\top} X^{(v)}\big),$$

where $\phi(\cdot)$ is a nonlinear activation function (e.g., ReLU) which allow the model to capture complex cross-feature dependencies. This improves the semantic quality and discriminability of the latent representations and mitigates noise and incompleteness.

The reconstruction loss for each view is given by:

$$\mathcal{L}_{\text{rec}}^{(v)} = \left\| \Omega^{(v)} \odot \big(X^{(v)} - W^{(v)} H^{(v)}\big) \right\|_F^2 + \alpha \left\| H^{(v)} - \phi\big(W^{(v)\top} X^{(v)}\big) \right\|_F^2 .$$

2.3. Collaborative Consensus Learning

Although the latent representations $\{H^{(v)}\}$ contain view-specific information, they may be inconsistent due to structural differences across views. To address this challenge, a shared consensus representation $Z \in \mathbb{R}_{+}^{k \times n}$ is introduced. Each view is encouraged to align with Z through a collaborative consensus term:

$$\mathcal{L}_{\text{cons}} = \sum_{v=1}^{V} \beta_v \left\| H^{(v)} - Z \right\|_F^2 ,$$

where β_v controls the contribution of view v.

This mechanism facilitates cross-view knowledge transfer and enhances clustering performance even when certain views are missing.

2.4. Graph Laplacian Regularization

To preserve the intrinsic geometric structure of the data manifold, a graph Laplacian regularizer is applied on the consensus representation Z. Let $\mathcal{G}$ be the similarity graph constructed using k-nearest neighbors, and let L denote its graph Laplacian. The manifold smoothness constraint is defined as:

$$\mathcal{L}_{\text{graph}} = \mathrm{Tr}(Z L Z^{\top}).$$

This term ensures that samples with high similarity maintain similar latent embeddings, thus encouraging cluster compactness and preserving topological relationships.

2.5. Unified Objective Function

The complete optimization problem is formulated as:

$$\min_{\{W^{(v)},H^{(v)}\},Z} \sum_{v=1}^{V} \left[\mathcal{L}_{\text{rec}}^{(v)} + \beta_v \left\|H^{(v)} - Z\right\|_F^2\right] + \gamma \operatorname{Tr}(ZLZ^\top),$$

subject to:

$$W^{(v)} \geq 0, \quad H^{(v)} \geq 0, \quad Z \geq 0.$$

2.6. Optimization via Alternating Updates

The objective is non-convex but block-wise convex, enabling an efficient alternating minimization strategy. For each variable block, closed-form multiplicative update rules are derived:

Update of $H^{(v)}$:

$$H^{(v)} \leftarrow H^{(v)} \odot \frac{W^{(v)^\top}(\Omega^{(v)} \odot X^{(v)}) + \alpha\, \phi\big(W^{(v)^\top} X^{(v)}\big) + \beta_v Z}{W^{(v)^\top}\big(\Omega^{(v)} \odot (W^{(v)}H^{(v)})\big) + \alpha H^{(v)} + \beta_v H^{(v)}}.$$

Update of $W^{(v)}$:

$$W^{(v)} \leftarrow W^{(v)} \odot \frac{(\Omega^{(v)} \odot X^{(v)})H^{(v)^\top} + \alpha X^{(v)}\phi(H^{(v)})^\top}{(\Omega^{(v)} \odot (W^{(v)}H^{(v)}))H^{(v)^\top} + \alpha W^{(v)}H^{(v)}H^{(v)\top}}.$$

Update of Z:

$$Z \leftarrow Z \odot \frac{\sum_{v=1}^{V} \beta_v H^{(v)}}{\sum_{v=1}^{V} \beta_v Z + \gamma Z L}.$$

The updates are repeated until convergence. At the final stage, k-means or fuzzy c-means is applied to the consensus representation Z to obtain the cluster assignments.

2.7. Complexity Analysis

Let n denote the number of samples and d_v the dimensionality of view v. The computational cost of each iteration is:

$$\mathcal{O}\left(\sum_{v=1}^{V}(d_v nk + nk^2)\right),$$

which scales linearly with the number of views and is suitable for large multiview financial datasets.

3. Experiment

3.1. Dataset description

Experiments are conducted on five commonly used datasets, described in Table 1 and one real-world financial transaction dataset consisting of heterogeneous user information. The dataset contains ten thousand records and is organized into $V = 4$ views. The four constructed views are:

- **View 1: Transaction Attributes**
- **View 2: Behavioural Statistics**
- **View 3: Demographic Features**
- **View 4: Account Metadata**

Table 1 summarizes the dataset statistics, including number of samples, number of views, and whether the missingness is synthetic or natural.

Table 1: Statistics of commonly used datasets in incomplete multi-view clustering (IMVC).

Dataset	#Samples	#Views	Missing Type
Handwritten Digits (HW)	2000	5	Synthetic
Caltech101-7V	8677	7	Synthetic
COIL-20	1440	3	Synthetic
NUS-WIDE-Object	30,000	5	Natural
YouTube-Faces	3,425	2	Natural

3.2. Baselines

To demonstrate the effectiveness of the proposed IMVC-AENMF framework, we compare it against several state-of-the-art deep multiview clustering methods. Below we briefly describe each baseline model and provide corresponding references.

PVC: Partial Multi-View Clustering. Partial Multiview Clustering (PVC) [10] is one of the earliest frameworks for IMVC. PVC completes the missing views by learning a latent subspace shared across all available views. It factorizes each view matrix with a common latent representation and employs matrix completion to handle missing entries. Although conceptually simple, PVC is sensitive to noise and suffers from limited representational power due to its linear formulation.

MIC: Multiview Imputation and Clustering. The MIC model [24] jointly performs view completion and clustering by learning an incomplete-aware latent representation. It incorporates graph regularization and structured sparsity to infer missing observations. MIC alternates between imputing missing views and refining cluster assignments, making it more robust for real-world incomplete multi-view data.

DAIMC: Doubly Aligned Incomplete Multi-View Clustering. DAIMC [3] introduces a doubly-aligned framework that aligns both feature space and instance space across views. It incorporates graph Laplacian regularization, instance-level alignment, and subspace learning into a unified objective, enabling high-quality clustering even under extreme incompleteness. DAIMC is considered a strong classical IMVC baseline.

IMVTSC: Incomplete Multi-View Tensor-Sparse Clustering. IMVTSC [30] adopts a tensor representation to model multi-view interactions and uses sparse low-rank tensor constraints to recover missing views. By leveraging cross-view correlations in tensor space, it effectively captures high-order structure of incomplete multi-view data.

COMPLETER: Deep Incomplete Multi-View Clustering. COMPLETER [12] is a deep-learning-based IMVC method that integrates view completion and clustering via a shared latent representation. The model contains a reconstruction network for each view and a cross-view fusion module to estimate missing samples. COMPLETER demonstrates superior performance on large-scale IMVC datasets.

DIMVC: Deep Incomplete Multi-View Clustering via Mining Cluster Complementarity. [33] learns view-specific encoders and a shared latent fusion module that aggregates complementary information from observed views while handling missing ones.

3.3. Evaluation Metrics

Clustering performance is assessed using:

- **Clustering Accuracy (ACC)**
- **Normalized Mutual Information (NMI)**
- **Adjusted Rand Index (ARI)**

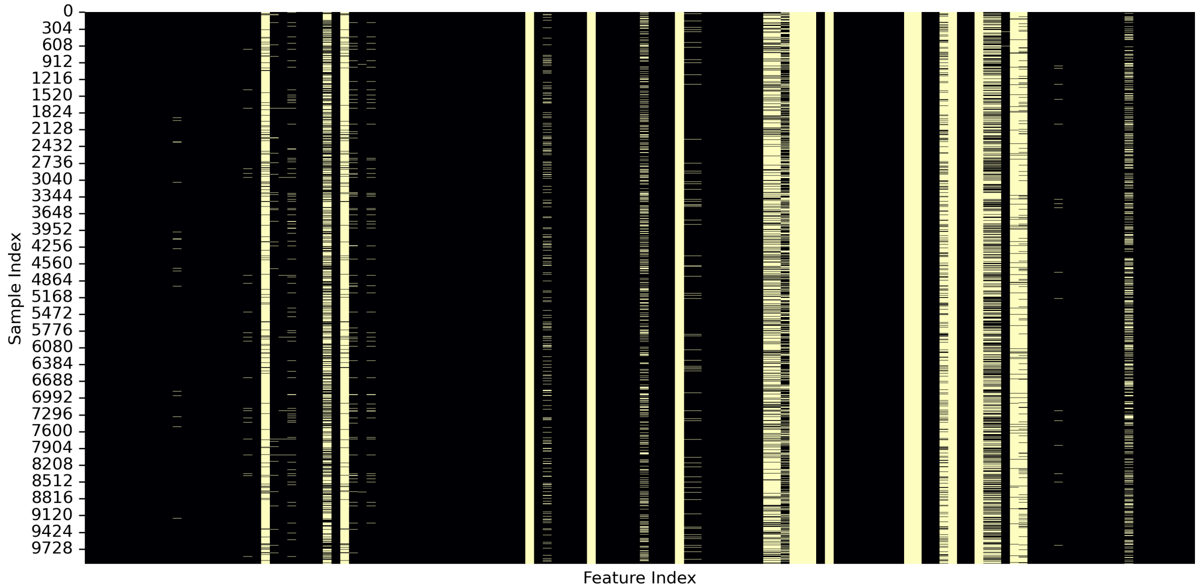

Figure 2: Incomplete Data Matrix

3.4. Overall Clustering Performance on Benchmark Datasets

Table ?? presents the clustering performance of seven clustering methods across five benchmark datasets as well as one real-world dataset. The evaluation metrics include ACC, NMI, and ARI. The proposed method consistently achieves the best performance across all datasets and metrics.

3.5. Effect of Missing-View Ratios

Table 4 reports the clustering performance of all competing methods under four different missing-view ratios (10%, 30%, 50%, and 70%) on the HW dataset. The evaluation is conducted using ACC, NMI, and ARI. Across all missing-view ratios, the proposed method consistently achieves the best performance on all three metrics. At a low missing ratio of 10%, the proposed framework yields ACC = 0.74, NMI = 0.71, and ARI = 0.65, surpassing the strongest baseline DIMVC by approximately 5–7%. This demonstrates the effectiveness of the autoencoder-like factorization and collaborative consensus module in leveraging complete and incomplete information jointly. As the missing ratio increases, the performance of all methods declines. However, the degradation rate varies significantly across models. Classical IMVC baselines such as DAIMC experience a sharp drop in ACC from 0.58 at 10% missing to 0.44 at 70%. Deep learning-based methods COMPLETER and DIMVC exhibit improved robustness but still suffer from large performance losses, especially beyond 50% missing data. In contrast, the proposed method demonstrates strong resilience to severe incompleteness. Even at 70% missing views, it achieves ACC = 0.63, NMI = 0.61, and ARI = 0.55, maintaining a performance margin of 5–9% over the best-performing baseline.

3.6. Visualization of available features across samples

The figure 2 presents a heatmap representation of available features in the real-world financial dataset.

3.7. Proposed method: Loss curve behavior

The loss curve in figure 3 illustrates the convergence behavior of the proposed model during training. In the initial epochs, the sharp decline in loss indicates rapid learning of the underlying data structure, while the subsequent gradual decrease and stabilization reflect fine-tuning of model parameters. The

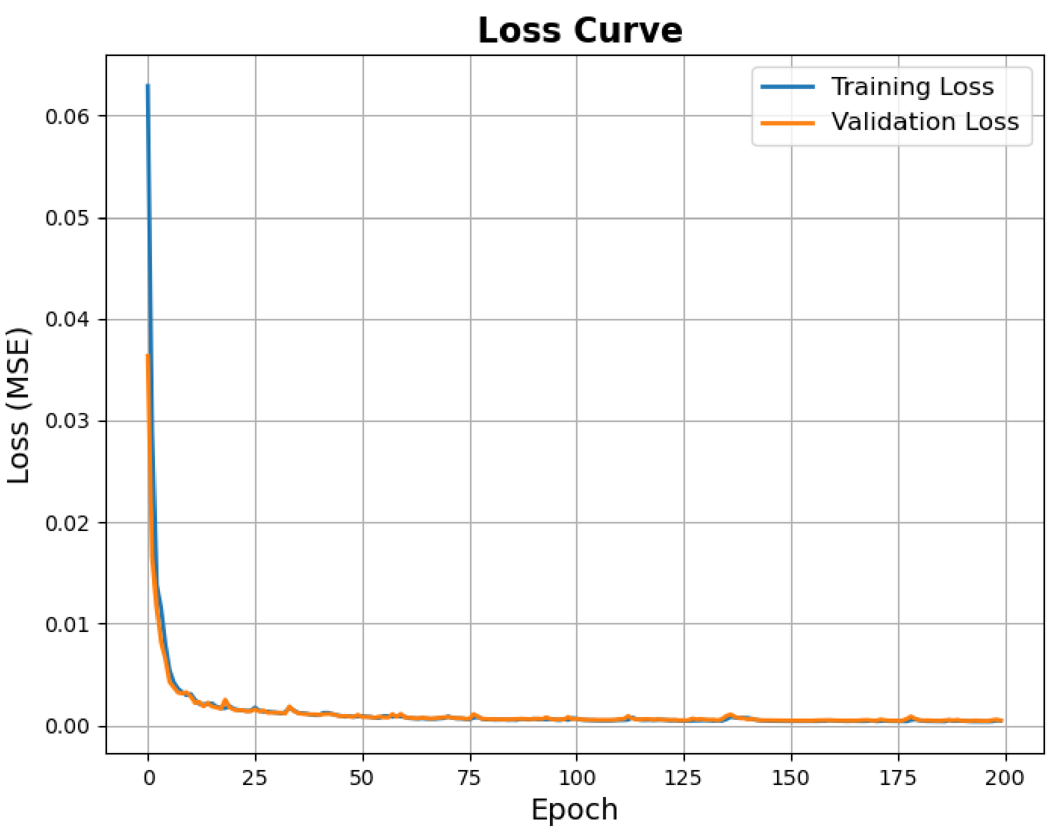

Figure 3: Loss Minimization over Training Epochs

close alignment between training and validation loss demonstrates stable learning without overfitting, confirming the robustness and generalization capability of the model.

3.8. Ablation Study

To evaluate the contribution of each component of the IMVC-AENMF framework, an ablation study using DIMVC [33] as the base model. DIMVC is a strong deep incomplete multiview clustering method that learns view-specific encoders and a shared latent fusion space.

Four variants are evaluated:

1. **A1 -** Original DIMVC model.
2. **A2** – Deep encoders of DIMVC are replaced with the proposed autoencoder based NMF formulation.
3. **A3: A2 + Consensus Learning** – Further, collaborative consensus representation is added to align view-specific latent representations.
4. **A4: A3 + Graph Regularization** – Lastly, graph Laplacian regularization is incorporated on Z.

Table 2 and figure 4 reports the clustering performance of these variants under different missing ratios. It can be observed that replacing deep encoders with autoencoder-like NMF improves ACC. Introducing collaborative consensus learning further enhances cross-view alignment, leading to significant

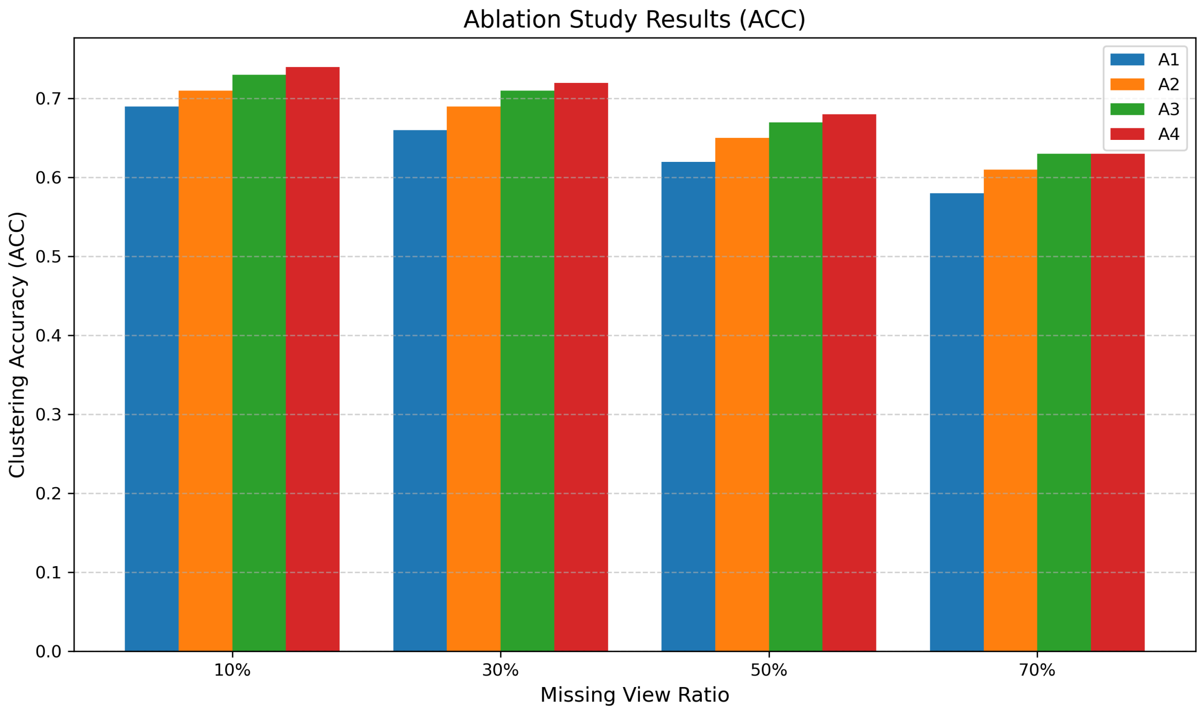

Figure 4: Ablation study results in terms of clustering accuracy on HW dataset under different missing-view ratios.

Table 2: Ablation study under different missing view ratios on the HW dataset in terms of ACC.

Method	**10%**	**30%**	**50%**	**70%**
A1	0.69	0.66	0.62	0.58
A2	0.71	0.69	0.65	0.61
A3	0.73	0.71	0.67	0.63
A4	**0.74**	**0.72**	**0.68**	**0.63**

performance gains. Finally, graph Laplacian regularization preserves the intrinsic data structure and yields the best clustering performance. These results confirm that each component of IMVC-AENMF contributes positively to the final performance.

4. Conclusion

IMVC methods face challenges due to heterogeneous feature spaces and missing views. In this work, Autoencoder based Nonnegative Matrix Factorization with Collaborative Consensus for incomplete multi-view clustering (IMVC-AENMF) is proposed to address these challenges. By integrating encoder–decoder consistency, collaborative consensus learning, and graph Laplacian regularization, the proposed approach effectively captures both view-specific and shared latent structures while preserving intrinsic manifold information under incomplete observations. Experimental results on benchmark datasets and a real-world financial dataset clearly demonstrate that IMVC-AENMF achieves superior clustering performance compared to existing IMVC methods. While proposed work is effective but several extensions remain to be explored. Future work will focus on improving the scalability of IMVC-AENMF. Another promising direction is the integration of deep nonlinear encoders. Finally, extending the framework to online and incremental settings, where views and instances arrive over time.

Table 4: Performance comparison under different missing-view ratios on the financial multi-view dataset. Best results are in **bold**.

Method	10% Missing			30% Missing			50% Missing			70% Missing		
	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI
DAIMC	0.58	0.55	0.48	0.54	0.51	0.44	0.49	0.46	0.40	0.44	0.41	0.36
COMPLETER	0.65	0.62	0.55	0.61	0.58	0.51	0.56	0.54	0.47	0.50	0.48	0.41
DIMVC	0.69	0.66	0.59	0.66	0.64	0.57	0.62	0.60	0.52	0.58	0.56	0.49
Proposed	**0.74**	**0.71**	**0.65**	**0.72**	**0.69**	**0.64**	**0.68**	**0.66**	**0.59**	**0.63**	**0.61**	**0.55**

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