# Novelty Assessment Report

**Paper**: Fairness-Aware Multi-view Evidential Learning with Adaptive Prior

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## Abstract

Multi-view evidential learning aims to integrate information from multiple views to improve prediction performance and provide trustworthy uncertainty estimation. Most previous methods assume that view-specific evidence learning is naturally reliable. However, in practice, the evidence learning process tends to be biased. Through empirical analysis on real-world data, we reveal that samples tend to be assigned more evidence to support data-rich classes, thereby leading to unreliable uncertainty estimation in predictions. This motivates us to delve into a new Biased Evidential Multi-view Learning (BEML) problem. To this end, we propose Fairness-Aware Multi-view Evidential Learning (FAML). FAML first introduces an adaptive prior based on training trajectories, which acts as a regularization strategy to flexibly calibrate the biased evidence learning process. Furthermore, we explicitly incorporate a fairness constraint based on class-wise evidence variance to promote balanced evidence allocation. In the multi-view fusion stage, we propose an opinion alignment mechanism to mitigate view-specific bias across views, thereby encouraging the integration of consistent and mutually supportive evidence. Theoretical analysis shows that FAML enhances fairness in the evidence learning process. Extensive experiments on six real-world multi-view datasets demonstrate that FAML achieves more balanced evidence allocation and improves both prediction performance and the reliability of uncertainty estimation compared to state-of-the-art methods.

## Core Task Landscape

This paper addresses: **Mitigating Evidential Bias in Multi-view Learning**

A total of **1 papers** were analyzed and organized into a taxonomy with **2 categories**.

### Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Fairness-Aware Evidential Learning with Adaptive Calibration**
- **Graph-Based Confidence Calibration Under Adversarial Conditions**

### Complete Taxonomy Tree

- Mitigating Evidential Bias in Multi-view Learning Survey Taxonomy
- Fairness-Aware Evidential Learning with Adaptive Calibration
  - Adaptive Prior-Based Evidence Regularization ★ (1 papers)
  - [0] Fairness-Aware Multi-view Evidential Learning with Adaptive Prior (Anon et al., 2026) View paper
- Graph-Based Confidence Calibration Under Adversarial Conditions
  - Multi-view Consistency Regularization for Graph Robustness (1 papers)
  - [1] A Multi-view Confidence-calibrated Framework for Fair and Stable Graph Representation Learning (Xu Zhang, 2021) View paper

### Narrative

Core task: Mitigating evidential bias in multi-view learning through fairness-aware uncertainty estimation. This field addresses the challenge of ensuring that multi-view learning systems produce fair and well-calibrated uncertainty estimates, particularly when different data views may introduce or amplify biases. The taxonomy reveals two main branches: one focused on fairness-aware evidential learning with adaptive calibration, which emphasizes methods that adjust evidence collection and uncertainty quantification to reduce bias across subgroups, and another centered on graph-based confidence calibration under adversarial conditions, which explores robustness and calibration in structured data settings where adversarial perturbations or distributional shifts may occur. These branches reflect complementary concerns—one prioritizing equitable treatment across views and demographic groups, the other emphasizing resilience to challenging or hostile data conditions.

Within the fairness-aware branch, a key theme is the development of adaptive mechanisms that regularize evidence based on learned priors, allowing models to dynamically balance uncertainty across views without over-relying on potentially biased sources. Fairness Evidential Learning[0] exemplifies this direction by introducing adaptive prior-based evidence regularization, aiming to ensure that uncertainty estimates remain fair even when individual views carry systematic biases. This approach contrasts with earlier work such as Fair Graph Representation[1], which addresses fairness in graph-structured data but does not explicitly incorporate evidential uncertainty frameworks. The central trade-off in this area involves maintaining high predictive performance while ensuring that uncertainty quantification does not disproportionately penalize underrepresented groups or views, a challenge that remains an active area of exploration.

## Related Works in Same Category

No sibling papers and no sibling subtopics were found under the same parent taxonomy node; the paper appears structurally isolated in the taxonomy.

## Contributions Analysis

**Overall novelty summary.** The paper addresses biased evidence allocation in multi-view evidential learning, proposing adaptive priors and fairness constraints to calibrate uncertainty estimation. According to the taxonomy, it occupies the 'Adaptive Prior-Based Evidence Regularization' leaf under 'Fairness-Aware Evidential Learning with Adaptive Calibration'. Notably, this leaf contains only the original

paper itself with no sibling papers, suggesting this specific combination of adaptive priors and fairness-aware evidence regularization represents a relatively unexplored research direction within the broader multi-view learning landscape.

The taxonomy reveals a sparse field structure with only two main branches and two leaf nodes total. The neighboring branch focuses on 'Graph-Based Confidence Calibration Under Adversarial Conditions', which addresses robustness in graph neural networks rather than general multi-view settings. The scope notes clarify that methods using consistency regularization without adaptive priors belong elsewhere, while the original paper's approach of training-trajectory-based adaptive priors distinguishes it from consistency-based calibration strategies. This positioning suggests the work bridges fairness concerns with evidential uncertainty in a relatively novel way.

Among 28 candidates examined, the contribution-level analysis reveals mixed novelty signals. The BEML problem formulation examined 10 candidates with none appearing to refute it, suggesting this framing may be relatively fresh. However, the training-trajectory-based adaptive prior mechanism examined 10 candidates and found 1 refutable match, indicating some overlap with existing adaptive prior work. The opinion alignment mechanism for multi-view fusion examined 8 candidates with no refutations, suggesting this fusion strategy may offer more distinctive technical contributions within the limited search scope.

Based on the top-28 semantic matches examined, the work appears to occupy a sparse research area with limited direct competition in its specific leaf. The taxonomy structure and contribution-level statistics suggest moderate novelty, though the analysis acknowledges its limited scope—a more exhaustive literature search across multi-view learning, evidential deep learning, and fairness-aware machine learning might reveal additional related work not captured in this focused examination.

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This paper presents **3 main contributions**, each analyzed against relevant prior work:

## Contribution 1: Biased Evidential Multi-view Learning (BEML) problem formulation

**Description**: The authors identify and formalize a previously neglected problem in multi-view evidential learning where the evidence learning process exhibits implicit unfairness, with samples tending to receive more evidence for data-rich classes, leading to unreliable uncertainty estimation.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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### 1. Towards robust uncertainty-aware incomplete multi-view classification
**URL**: View paper

**Brief Assessment**

Robust Incomplete Multiview[3] addresses uncertainty and conflicts in incomplete multi-view classification using evidential deep learning, but does not identify or formalize the specific problem of implicit unfairness in evidence learning where samples receive more evidence for data-rich classes. The candidate focuses on handling missing views and conflicting evidence through imputation and conflict-aware fusion, which is a different technical challenge than the fairness-based evidence allocation bias identified in the original paper.

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### 2. Multi-scale modeling and uncertainty quantification of weather and language
**Brief Assessment**

Multiscale Weather Language[8] focuses on multi-scale modeling of weather and language systems with uncertainty quantification through statistical distributions, not on fairness issues in multi-view evidential learning or evidence allocation bias across classes.

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### 3. Enhancing Multi-view Open-set Learning via Ambiguity Uncertainty Calibration and View-wise Debiasing
**URL**: View paper

**Brief Assessment**

Ambiguity Calibration Debiasing[9] addresses view-induced bias in open-set scenarios, not evidential learning bias in class-imbalanced settings. The candidate focuses on open-set recognition with unknown classes, while the original addresses evidence allocation fairness across known classes.

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### 4. EviGraph-LLMRec: Evidential Graph-Language Model Fusion for Uncertainty-Aware Recommendation
**URL**: View paper

**Brief Assessment**

EviGraph-LLMRec[4] focuses on graph-language model fusion for recommendation systems with uncertainty quantification. The candidate does not address multi-view evidential learning or evidence allocation fairness across classes, which is the core focus of the original paper's BEML problem formulation.

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### 5. Active learning with complementary sampling for instructing class-biased multi-label text emotion classification
**URL**: View paper

**Brief Assessment**

Complementary Sampling Emotion[10] addresses class imbalance in multi-label text emotion classification through active learning, not multi-view evidential learning with uncertainty estimation bias.

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### 6. FairRisk-Rec: Fairness-Aware Uncertainty-Calibrated Recommendation with Evidence-Guided Bias Mitigation
**URL**: View paper

**Brief Assessment**

FairRisk Recommendation[2] focuses on fairness-aware recommendation systems with uncertainty calibration, not multi-view evidential learning. The candidate addresses bias mitigation in recommendation contexts, while the original paper identifies unfairness in multi-view evidence learning processes—these are distinct problem domains.

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### 7. Enhancing Adaptive Deep Networks for Image Classification via Uncertainty-aware Decision Fusion
**URL**: View paper

**Brief Assessment**

Uncertainty Decision Fusion[6] addresses adaptive deep networks with multiple classifier heads in single models, not multi-view learning with evidence bias across different data views. The technical contexts are fundamentally different.

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### 8. Beyond Equal Views: Strength-Adaptive Evidential Multi-View Learning
**URL**: View paper

**Brief Assessment**

Strength Adaptive Evidential[7] addresses a different problem: unequal view strength during fusion, not evidence allocation bias across classes. The candidate focuses on view-level contribution weighting, while the original identifies class-level evidence unfairness.

### 9. A Multi-view Confidence-calibrated Framework for Fair and Stable Graph Representation Learning

**URL**: View paper

**Brief Assessment**

Fair Graph Representation[1] focuses on fairness and stability in graph neural networks with multi-view uncertainty calibration, not on the BEML problem of biased evidence allocation across data-rich vs. data-poor classes in general multi-view evidential learning.

### 10. Discovering features with synergistic interactions in multiple views

**URL**: View paper

**Brief Assessment**

Synergistic Feature Discovery[5] focuses on discovering synergistic and non-synergistic feature interactions across multiple views using information-theoretic concepts, not on unfairness in evidential learning or uncertainty estimation bias in multi-view settings.

## Contribution 2: Training-trajectory-based adaptive prior mechanism

**Description**: The authors propose an adaptive prior mechanism that adjusts Dirichlet distribution parameters based on class-wise performance during training, providing compensatory support to poorly performing classes and promoting balanced evidence allocation across different classes.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

### 1. Adaptive robust evidential optimization for open set detection from imbalanced data

**URL**: View paper

**Prior Art Analysis**

Robust Evidential Optimization[13] demonstrates prior work on adaptive priors for evidential learning under imbalanced data. The candidate paper introduces an adaptive prior mechanism that adjusts Dirichlet distribution parameters based on class-wise performance during training, specifically designed to handle class imbalance. This directly addresses the same problem space as the original paper's training-trajectory-based adaptive prior, which also adjusts Dirichlet parameters based on class-wise performance to promote balanced evidence allocation. Both papers modify the standard uniform prior ($\beta=1$) in evidential deep learning to address bias in evidence learning under imbalanced conditions.

**Evidence**

Evidence 1 - **Rationale**: Both papers propose adaptive mechanisms that adjust priors during training based on performance. The candidate's multi-scheduler function adaptively controls the uncertainty set size based on training progress, which indirectly adjusts how evidence is allocated across classes, similar to the original's trajectory-based prior adjustment. - **Original**: we introduce the training-trajectory-based prior into the construction of dirichlet parameters, adaptively calibrating the prior support assigned to each class during training, thereby promoting balanced evidence allocation. with this adaptive design, the prior directly reflects class-wise performan... - **Candidate**: to address this key challenge, we propose to conduct multi-scheduler learning to automatically construct a composite scheduler function that can be automatically learned for each given dataset to deliver the optimal training behavior. more specifically, the multi-scheduler function ( msf) is formula...

Evidence 2 - **Rationale**: Both papers move away from fixed uniform priors in evidential learning. The original explicitly modifies Dirichlet priors based on learning history, while the candidate adaptively adjusts the uncertainty set size (which affects evidence allocation) based on training progress through msf. - **Original**: instead of employing a uniform dirichlet prior in parameterizing the dirichlet distribution, our approach adjusts the prior adaptively based on the learning history of each class. - **Candidate**: by leveraging the proposed msf to control the size of the uncertainty set, we can achieve adaptive robust training. let $\eta_0$ be the initial size of the uncertainty set and the size of the set at epoch t is $\eta_t = \eta_{t-1}$ msf(w, $\beta$, t, t)

### 2. Evidential Federated Learning for Skin Lesion Image Classification

**URL**: View paper

**Brief Assessment**

Evidential Federated Lesion[15] focuses on federated learning for skin lesion classification with class-frequency-weighted priors, not training-trajectory-based adaptive priors that adjust based on class-wise performance during training as in the original paper.

### 3. Evidentially calibrated source-free time-series domain adaptation with temporal imputation

**URL**: View paper

**Brief Assessment**

Evidential Temporal Adaptation[14] focuses on source-free time-series domain adaptation with evidential uncertainty estimation, not on adaptive priors for calibrating evidence learning in imbalanced classification across multiple views.

### 4. Multi-view deep evidential fusion neural network for assessment of screening mammograms

**URL**: View paper

**Brief Assessment**

Evidential Fusion Mammograms[16] focuses on multi-view mammogram classification using fixed uniform priors in Dirichlet distributions, without any adaptive prior mechanism based on training trajectories or class-wise performance adjustments.

### 5. Multiple adaptive over-sampling for imbalanced data evidential classification

**URL**: View paper

**Brief Assessment**

Adaptive Oversampling Evidential[11] focuses on over-sampling techniques for imbalanced data in evidential classification, not on adaptive priors for calibrating evidence learning during training trajectories.

### 6. Revisiting essential and nonessential settings of evidential deep learning

**URL**: View paper

**Brief Assessment**

Revisiting Evidential Learning[12] focuses on relaxing nonessential settings in evidential deep learning (e.g., fixed prior weights, variance-minimizing terms) rather than proposing adaptive priors for class-imbalanced scenarios. The candidate does not address training-trajectory-based mechanisms or fairness-aware evidence allocation across classes.

### 7. Multi-Annotator Consensus Network with Adaptive Preprocessing for Lung Nodule Segmentation: A Deep Learning Framework for Clinical Decision Support

**URL**: View paper

**Brief Assessment**

Consensus Nodule Segmentation[17] focuses on multi-annotator consensus learning for lung nodule segmentation in medical imaging, not on adaptive priors for calibrating evidence learning in imbalanced classification tasks as proposed in the original paper.

### 8. Evidential Deep Learning for High-Confidence Sample Selection in Noisy Label Learning

**URL**: View paper

**Brief Assessment**

Evidential Sample Selection[18] focuses on sample selection in noisy label learning scenarios. The provided context does not contain sufficient technical detail about adaptive priors or evidence calibration mechanisms to assess overlap with the original paper's training-trajectory-based adaptive prior for multi-view evidential learning.

### 9. Quantifying Water Content of a Landfill With ERT Data by Bayesian Evidential Learning

**URL**: View paper

**Brief Assessment**

Bayesian Evidential Landfill[20] addresses water content estimation in landfills using Bayesian evidential learning with ERT data, focusing on geophysical applications rather than multi-view classification with adaptive priors for imbalanced classes.

### 10. Evidential Deep Learning with Reweighted Margin Adjustment for Uncertainty-Driven Cervical OCT Image Diagnosis

**URL**: View paper

**Brief Assessment**

Evidential Cervical OCT[19] addresses class imbalance in cervical OCT image classification through a reweighted margin adjustment strategy, not a training-trajectory-based adaptive prior. The candidate focuses on medical imaging applications rather than general multi-view evidential learning frameworks.

## Contribution 3: Opinion alignment mechanism for multi-view fusion

**Description**: The authors design a mechanism that minimizes discrepancies between view-specific opinions during the fusion stage, ensuring different views align on both predictions and confidence levels to reduce view-specific bias in the final decision.

This contribution was assessed against **8 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

### 1. Energy-based Deep Incomplete Multi-View Clustering

**URL**: View paper

**Brief Assessment**

Energy Incomplete Clustering[28] focuses on incomplete multi-view clustering with missing views, using energy-based selective imputation and contrastive alignment. The original paper addresses multi-view evidential learning with complete views, designing an opinion alignment mechanism to minimize discrepancies between view-specific opinions during fusion. These are fundamentally different technical approaches for different problem settings.

### 2. Enhancing Multi-view Open-set Learning via Ambiguity Uncertainty Calibration and View-wise Debiasing

**URL**: View paper

**Brief Assessment**

Ambiguity Calibration Debiasing[9] uses uniform averaging across views and HSIC-based debiasing to suppress view-specific biases, not opinion alignment that minimizes discrepancies between view-specific predictions and confidence levels as described in the original paper.

### 3. Interpretable multi-view fusion network via multi-view dual alignment and private bias filtering for Alzheimer's disease analysis

**URL**: View paper

**Brief Assessment**

Cannot assess refutation potential as the candidate paper's full text context is marked 'n/a'. No textual evidence is available for comparison.

### 4. Multi-View Clustering via Multi-Stage Fusion

**URL**: View paper

**Brief Assessment**

Multistage Fusion Clustering[26] focuses on multi-view clustering (unsupervised learning) with late/early fusion stages, not on evidential learning with opinion alignment for bias reduction in classification tasks.

### 5. Deep incomplete multi-view clustering with cross-view partial sample and prototype alignment

**URL**: View paper

**Brief Assessment**

Incomplete Prototype Alignment[24] focuses on incomplete multi-view clustering with prototype alignment across views, not on aligning view-specific opinions during fusion to reduce bias in evidential learning frameworks.

### 6. Multi-view graph convolutional network for multimedia recommendation

**URL**: View paper

**Brief Assessment**

Multiview Graph Recommendation[22] focuses on multimedia recommendation systems with modality-specific features (visual, textual) and designs a behavior-aware fuser to adaptively weight different modalities. This is fundamentally different from the original paper's opinion alignment mechanism, which operates on evidential learning frameworks to minimize discrepancies between view-specific Dirichlet distributions and their associated uncertainty estimates to reduce bias in multi-view fusion.

### 7. Reliable conflictive multi-view learning

**URL**: View paper

**Brief Assessment**

Conflictive Multiview Learning[21] focuses on handling conflictive multi-view data where views show contradictory information, using a conflictive opinion aggregation strategy that increases uncertainty when views conflict. The original paper's opinion alignment mechanism aims to minimize discrepancies to reduce view-specific bias, which is a fundamentally different technical approach and problem setting.

### 8. DPFMVC: Dynamic Progressive Fusion for Multi-view Clustering

**URL**: View paper

**Brief Assessment**

Dynamic Progressive Fusion[23] focuses on multi-view clustering with view-adaptive fusion and progressive fusion strategies, not on aligning view-specific opinions to reduce bias in evidential learning frameworks. The technical contexts differ fundamentally: clustering vs. evidential classification with uncertainty estimation.

## Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

## References

- [0] Fairness-Aware Multi-view Evidential Learning with Adaptive Prior View paper
- [1] A Multi-view Confidence-calibrated Framework for Fair and Stable Graph Representation Learning View paper
- [2] FairRisk-Rec: Fairness-Aware Uncertainty-Calibrated Recommendation with Evidence-Guided Bias Mitigation View paper
- [3] Towards robust uncertainty-aware incomplete multi-view classification View paper
- [4] EviGraph-LLMRec: Evidential Graph-Language Model Fusion for Uncertainty-Aware Recommendation View paper
- [5] Discovering features with synergistic interactions in multiple views View paper
- [6] Enhancing Adaptive Deep Networks for Image Classification via Uncertainty-aware Decision Fusion View paper
- [7] Beyond Equal Views: Strength-Adaptive Evidential Multi-View Learning View paper
- [8] Multi-scale modeling and uncertainty quantification of weather and language
- [9] Enhancing Multi-view Open-set Learning via Ambiguity Uncertainty Calibration and View-wise Debiasing View paper
- [10] Active learning with complementary sampling for instructing class-biased multi-label text emotion classification View paper
- [11] Multiple adaptive over-sampling for imbalanced data evidential classification View paper
- [12] Revisiting essential and nonessential settings of evidential deep learning View paper
- [13] Adaptive robust evidential optimization for open set detection from imbalanced data View paper
- [14] Evidentially calibrated source-free time-series domain adaptation with temporal imputation View paper
- [15] Evidential Federated Learning for Skin Lesion Image Classification View paper
- [16] Multi-view deep evidential fusion neural network for assessment of screening mammograms View paper
- [17] Multi-Annotator Consensus Network with Adaptive Preprocessing for Lung Nodule Segmentation: A Deep Learning Framework for Clinical Decision Support View paper
- [18] Evidential Deep Learning for High-Confidence Sample Selection in Noisy Label Learning View paper
- [19] Evidential Deep Learning with Reweighted Margin Adjustment for Uncertainty-Driven Cervical OCT Image Diagnosis View paper
- [20] Quantifying Water Content of a Landfill With ERT Data by Bayesian Evidential Learning View paper
- [21] Reliable conflictive multi-view learning View paper
- [22] Multi-view graph convolutional network for multimedia recommendation View paper
- [23] DPFMVC: Dynamic Progressive Fusion for Multi-view Clustering View paper
- [24] Deep incomplete multi-view clustering with cross-view partial sample and prototype alignment View paper
- [25] Mitigating world biases: A multimodal multi-view debiasing framework for fake news video detection View paper
- [26] Multi-View Clustering via Multi-Stage Fusion View paper
- [27] Interpretable multi-view fusion network via multi-view dual alignment and private bias filtering for Alzheimer's disease analysis View paper
- [28] Energy-based Deep Incomplete Multi-View Clustering View paper
- [29] CaRF: Enhancing Multi-View Consistency in Referring 3D Gaussian Splatting Segmentation View paper