Exploring Fusion Techniques in Multimodal AI-Based Recruitment: Insights from FairCVdb

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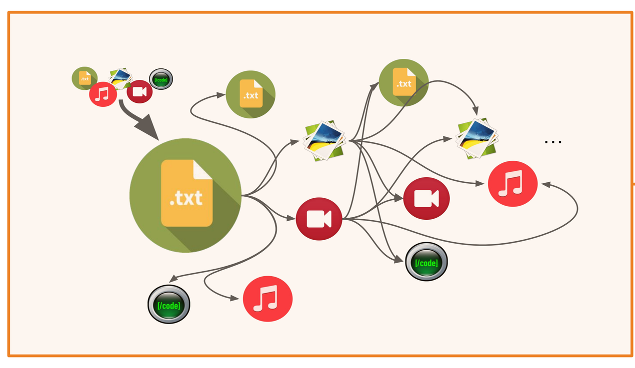
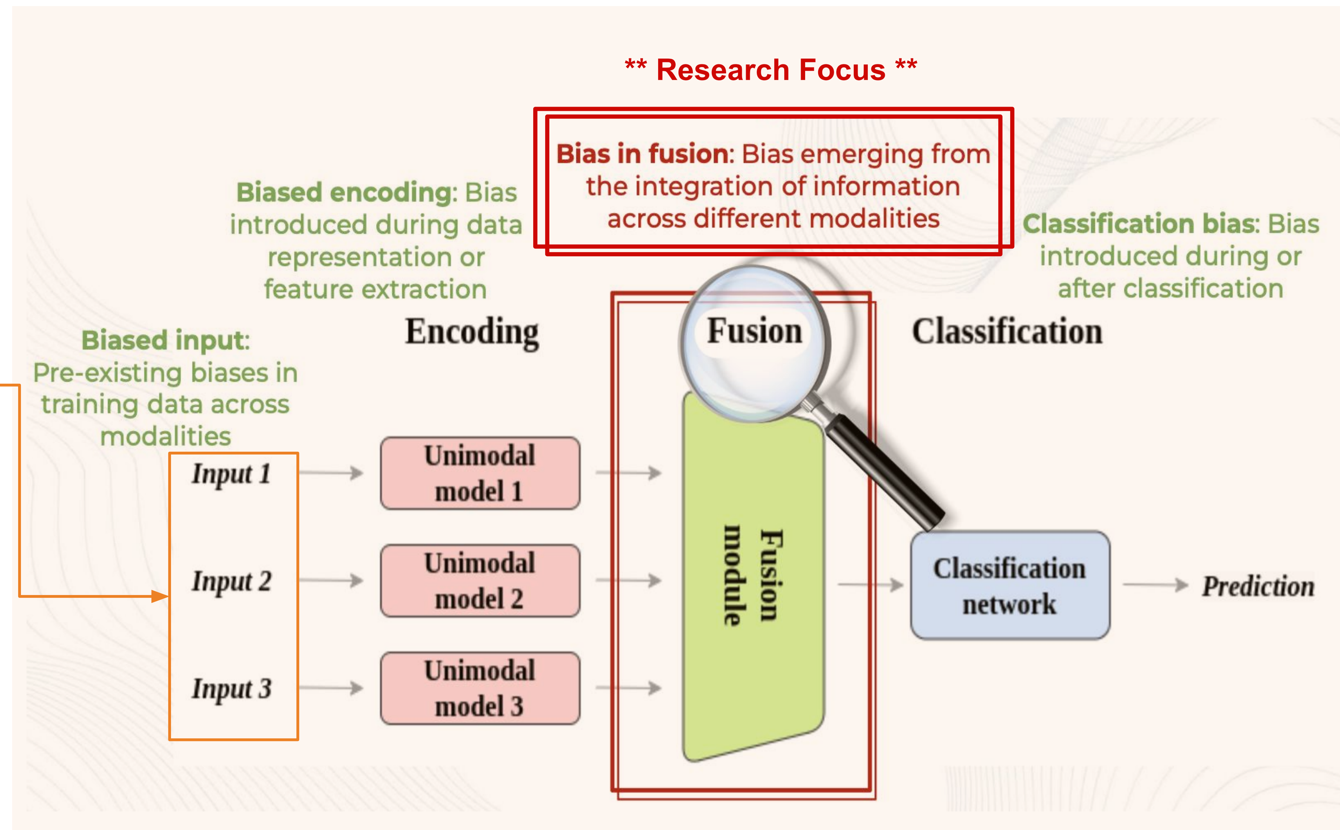
INTRODUCTION & MOTIVATION

Research Objective: Investigate the **fairness and bias implications of Fusion Approaches** in multimodal AI-based systems.



The concept of Multimodal learning involves data from different modalities.



Bias across stages of multimodal learning.

The Real-World Application: Multimodal AI-based recruitment systems:

700+ companies are using AI-based recruitment systems[1].

- Increasing use of decision-making algorithms raises concerns about transparency and discrimination, especially affecting specific social groups.
- Investigating how sensitive elements and internal biases influence current multimodal algorithms is crucial.

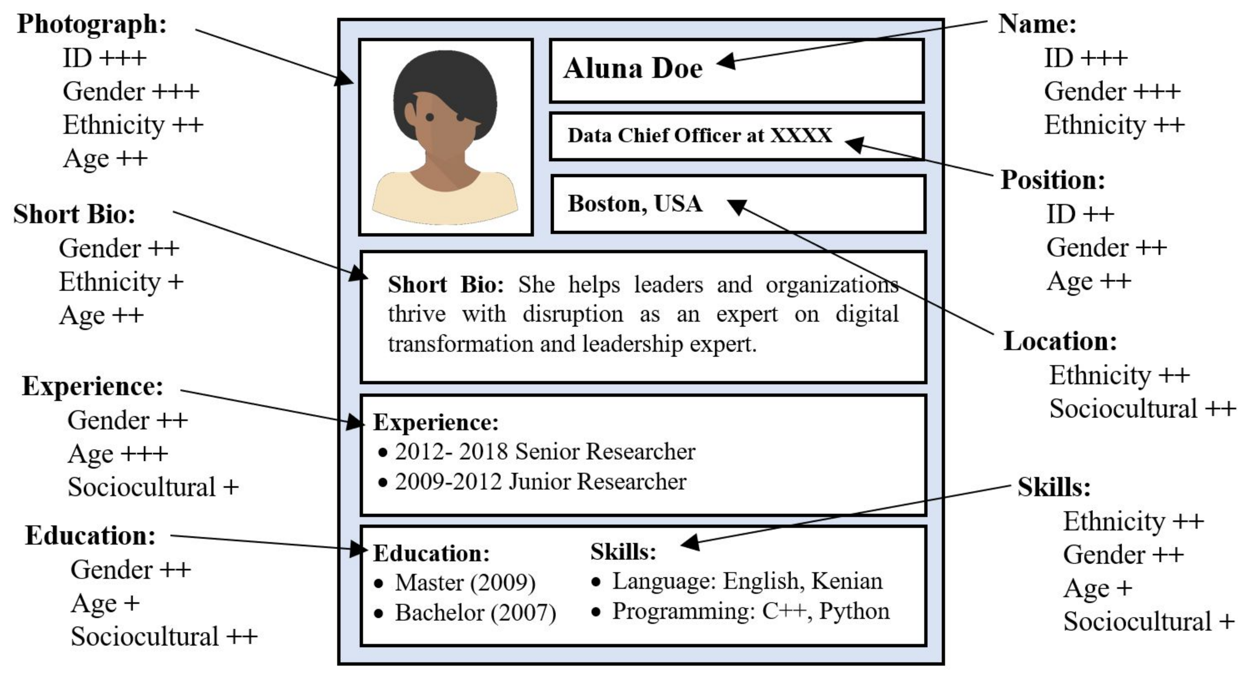
[1] Harwell, Drew. "A face-scanning algorithm increasingly decides whether you deserve the job." *Ethics of Data and Analytics*. Auerbach Publications, 2022. 206-211.

EXPERIMENTAL SETUP

Dataset: FairCVdb[2] for fairness study:

- **Synthetic** research dataset: **24,000** profiles.
- Contains **rich multimodal information** tailored to assess fairness and bias aspects in AI-driven recruitment algorithms.
- **Modalities**: **Visual** (Image), **Tabular** (attributes generated from US Census 2018 Education Attainment data), **Textual** (Short Bio).
- **Protected attributes**:
  - **Gender**: Female, Male.
  - **Ethnicity**: Asian, Caucasian, African-American.

Task: Determining whether the subject should be invited for a job interview.



Information blocks in a resume and personal attributes that can be derived from each one. The number of crosses represent the level of sensitive information (+++ = high, ++ = medium, + = low)

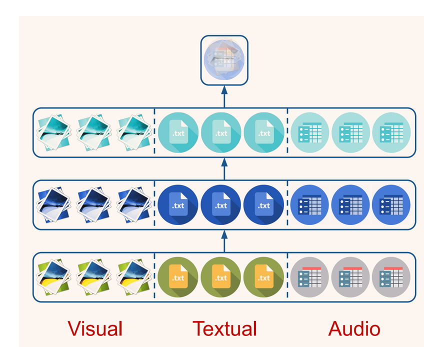
Evaluation Metrics: Mean Absolute Error (MAE) to measure accuracy. Kullback-Leibler (KL) divergence to measure biases between demographic distributions. Gender: compare and report the score distributions for males and females. Ethnicity: compute pairwise comparisons and report the average divergence.

Methodology: Recruitment model to predict scores based on candidate resumes, following the methodology from Peña et al. (2023)[3].

[2] Pena, Alejandro, et al. "Bias in multimodal AI: Testbed for fair automatic recruitment." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops. 2020.
[3] A. Peña, I. Serna, A. Morales, J. Fierrez, A. Ortega, A. Herrarte, M. Alcantara, J. Ortega-Garcia, Human-centric multimodal machine learning: Recent advances and testbed on ai-based recruitment, SN Computer Science 4 (2023) 434.

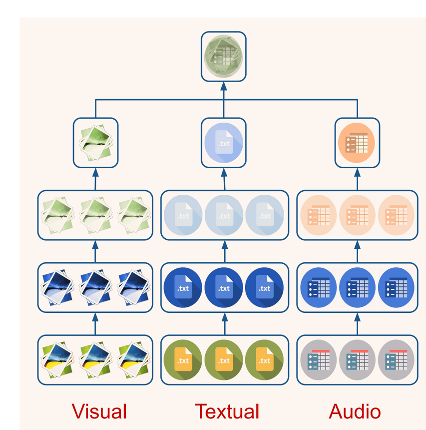
Fusion Strategies: Early and **Late**:

- **Early Fusion** (Feature-Level Fusion): Early fusion occurs at beginning, typically before the data is fed into a neural network.
- Advantageous when the relationships between different modalities are simple.



Early fusion

- **Late Fusion** (Classifier-Level Fusion): Late fusion occurs at the final decision-making stage, after each modality has been processed separately and the decision scores have been calculated.
- Advantageous when modalities have very different data characteristics.

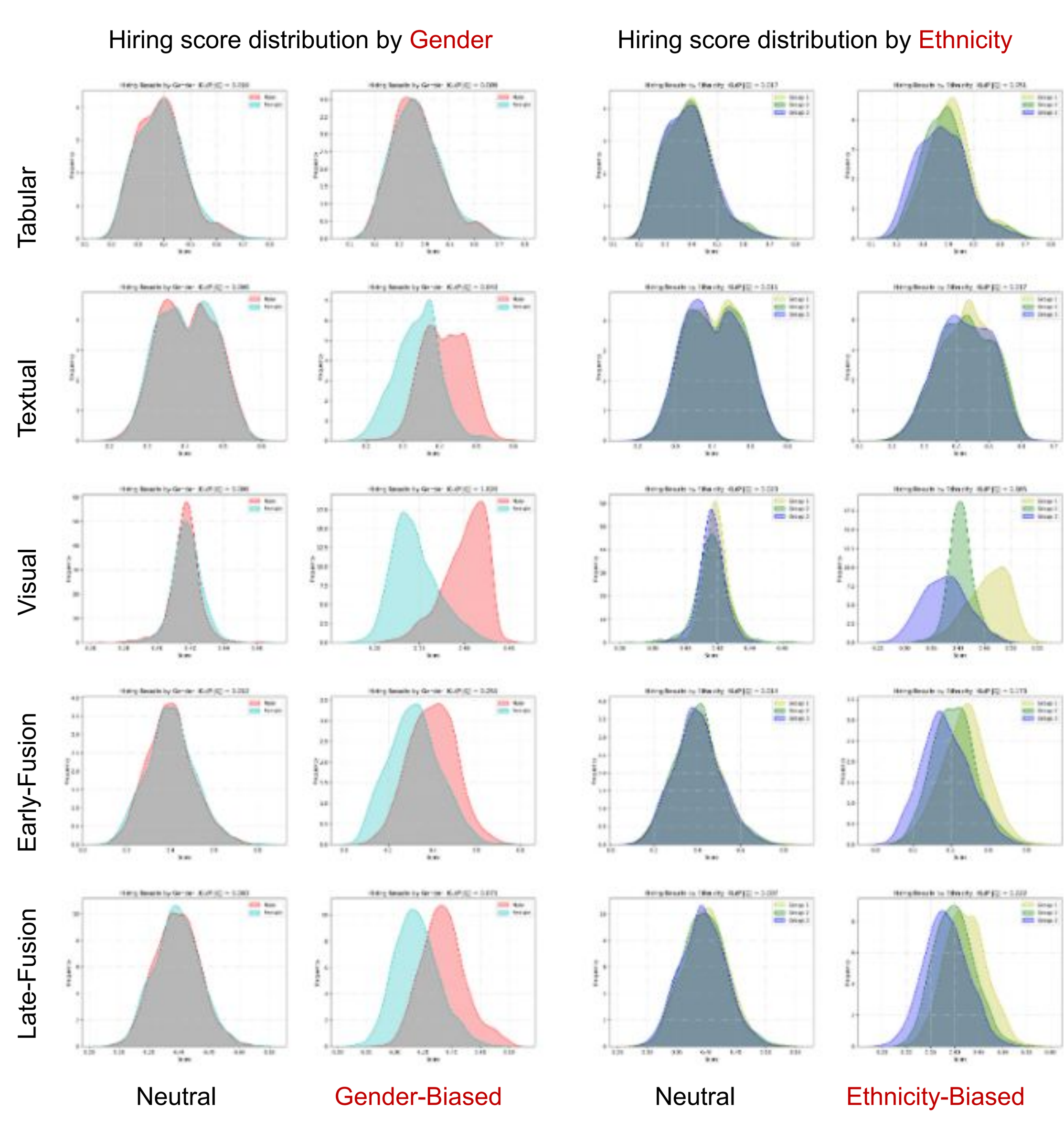


Late fusion

RESULTS & CONCLUSION

KL-divergence between score distributions across Gender and Ethnicity demographics:

- **Neutral**: models trained on unbiased neutral scores.
- **Gender/Ethnicity-Biased**: models trained on Gender/Ethnicity biased scores.
- **Tabular, Textual,** and **Visual**: models trained exclusively on tabular data, textual data, and visual data, respectively.
- **Early-Fusion** and **Late-Fusion**: models that integrate all three modalities at the data representation level and the decision level, respectively.
- **Interpretation**: Lower KL-divergence signifies closer alignment between distributions across various demographics, implying more fairness in hiring.



KL-divergence between score distributions across Gender and Ethnicity demographics.

Key Conclusions:

- Fusion techniques play a crucial role in addressing fairness and bias concerns in AI-based systems.
- Late fusion excels in unbiased ideal conditions, fostering fair decisions. However, it may exacerbate biases under biased conditions by independently learning biased models for each modality fostering undesired correlations.
- Early fusion often leads to fairer outcomes, especially with carefully chosen modalities.
- Not all fusion strategies are universally effective. Models trained solely on tabular data outperformed those using late fusion of multiple modalities in both accuracy and fairness.
- Fusing textual and visual modalities provides richer context and information, resulting in more accurate and fairer outcomes compared to using these modalities individually.
- Assessing the inherent risks of using simulated or synthetic data is crucial to ensuring fairness, transparency, and effectiveness in automated processes.

Future Directions:

- Diversify Fusion Strategies: Investigate beyond traditional early and late fusion techniques to uncover new insights for enhancing fairness in multimodal AI systems.
- Examine Generalisability: Test the applicability of these findings across various datasets and domains beyond hiring to broaden the study's impact and relevance.

For code and additional insights, visit: https://github.com/Swati17293/Multimodal-AI-Based-Recruitment-FairCVdb **or write to:** swati.swati@unibw.de

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