

GNN and LLM Insights: Multimodal Cues and Gender Disparities in Video Conversations

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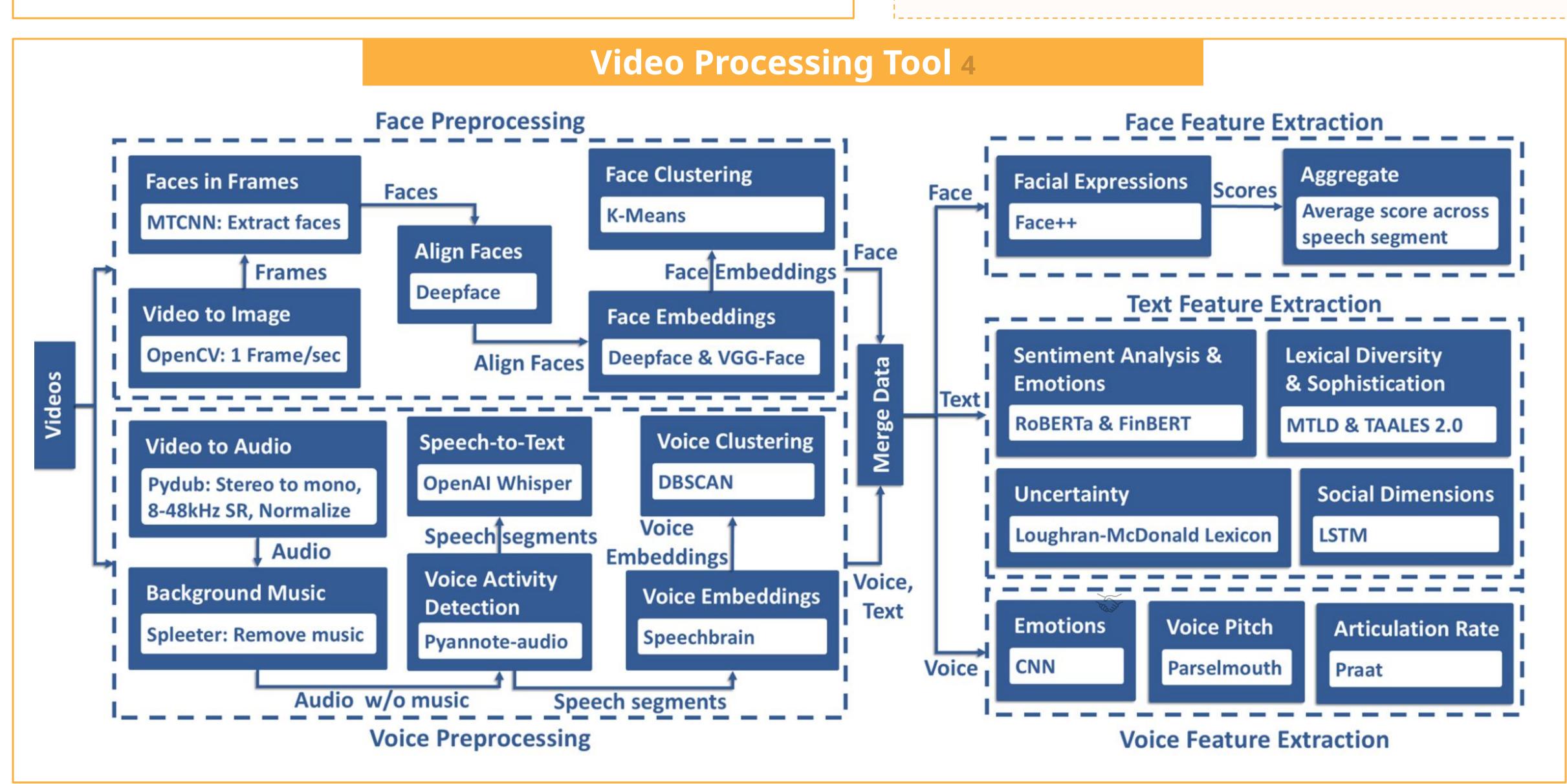
Motivation 1 ■ Interpersonal conversations shape major decisions: from investor funding pitches to job interviews; yet understanding what truly influences these outcomes is challenging. ■ Multimodal signals like facial expressions, voice tone, and spoken words interact dynamically, making it complex to detect their exact relation

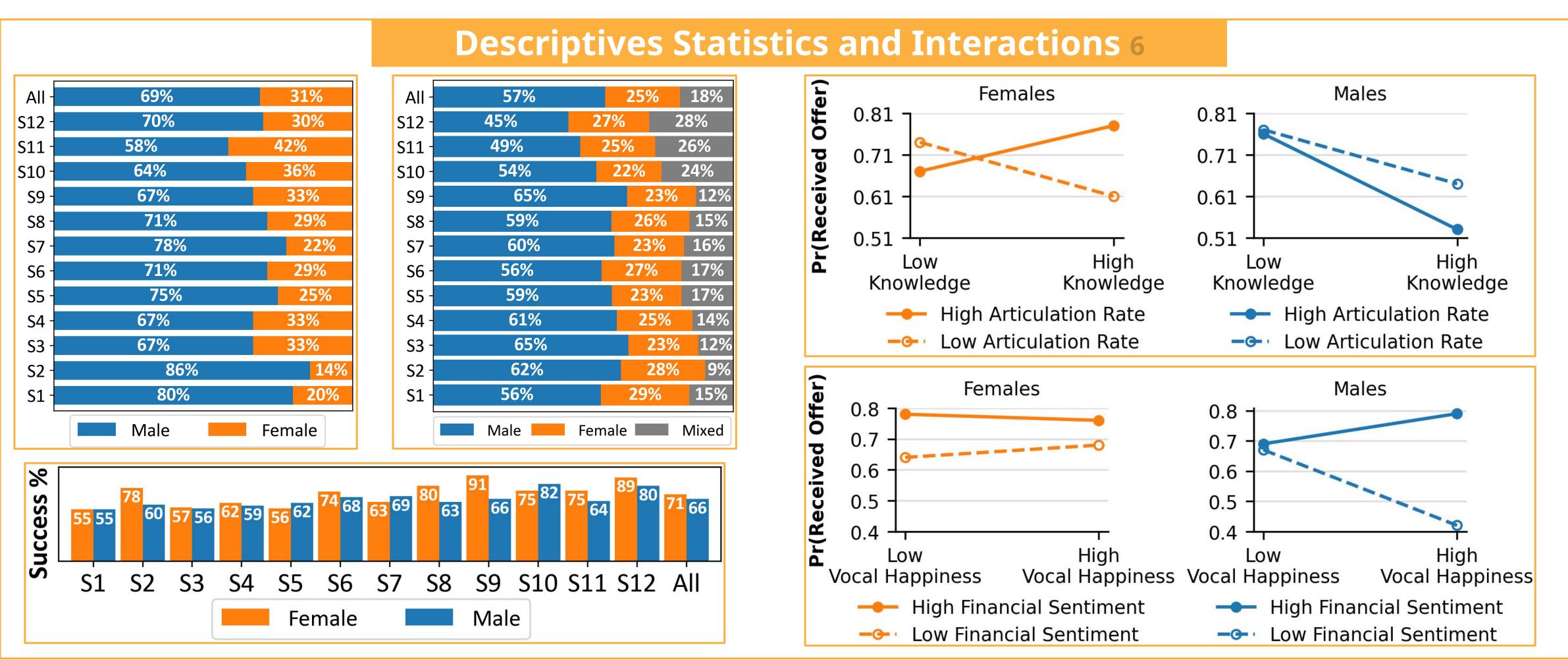
- Most of the existing research study these signals in isolation, missing
- Crucially, biases (e.g., gender biases) may hide in these subtle multimodal interactions, potentially disadvantaging specific groups.

critical interactions and temporal dynamics.

Contributions 2 **Research Question** "Do multimodal cues (visual, vocal, and verbal) affect investment decisions differently for men vs women?" ■ End-to-end pipeline that turns raw unstructured video conversations into 30 multimodal cues + rich controls ■ Graph Neural Network (GNN) tailored to conversational chronology; CAPTUM + GNNExplainer for transparency ■ Comprehensive bias audit across models.

Variables 3 **Independent Variables** Audio: Voice Emotions, Voice Pitch, Voice Articulation Rate Image: Facial Expressions Text: Sentiment Analysis & Text Emotions, Social Dimensions in Conversation, Lexical Diversity & Sophistication, Uncertainty Dependent Variable • Receive funding: whether a company has been offered funding or not, with values 1 and 0 respectively (binary)





Graph Neural Network 5 Graph Neural Network (GNN) – Graph Classification **Conversation as Graph** Graphs GCNConv GCNConv Features Features Features [f1,..., fN] [f1,..., fN] [f1,..., fN] **Female & Male Model Evaluation** [Graphs] Sklearn: Stratified K- fold & HPO Trained Model Trained Model **Feature Importance Unpaired T-Test** Explainable Al Compare the importance of features between Pytorch males and females **Feature Importance**

Performance Evaluation

GNN vs GPT-4 7

Model Precision Recall GNN - Vocal (F) 0.70 ± 0.07 0.63 ± 0.03 0.64 ± 0.03 0.60 ± 0.03 0.60 ± 0.04 GNN - Vocal (M) 0.64 ± 0.04 GNN - Facial (F) 0.65 ± 0.07 0.61 ± 0.05 0.61 ± 0.07 GNN - Facial (M) 0.60 ± 0.03 0.64 ± 0.03 0.60 ± 0.02 0.67 ± 0.04 GNN - Verbal (F) 0.69 ± 0.05 0.66 ± 0.04 0.57 ± 0.11 GNN - Verbal (M) 0.72 ± 0.05 0.69 ± 0.06 GNN - All (F) 0.70 ± 0.06 0.67 ± 0.02 0.69 ± 0.04 0.66 ± 0.02 GNN - All (M)

Table 3	3: Performance	e of GNNs usi	ing Stratified	5-fold CV

F: Females, M: Males

Precision	Recall	F1
0.794	0.435	0.562
0.736	0.404	0.521
	0.794	0.794 0.435

- **Experiment Setup**
- Anonymise pitch (Prompt 1) → present twice: no gender (Prompt 2) vs gender revealed (Prompt 3).
- GPT-4 Turbo (9 Apr 2024), temperature 0; outcome = Funded / Not Funded
- Statistical tests: F1, unpaired t-tests, logistic interaction.

Bias Evaluation

	Males		Females		t	p-value
	Mean	SD	Mean	SD		
GNN-All	0.736	0.441	0.739	0.440	-0.093	0.926

Table 4: Two-sample unpaired t-test to compare the	predic-
tions of GNN between males and females	

	Males		Females		t	p-value
	Mean	SD	Mean	SD		
W/O Gender	0.359	0.480	0.391	0.489	-0.877	0.381
W/ Gender	0.423	0.494	0.556	0.498	-3.619	0.000

Table 6: Two-sample unpaired t-test to compare the predictions of GPT-4 between males and females