The British University in Egypt

Faculty of Informatics & Computer Science

InSightHire

Revolutionizing Candidate Assessment: A Comprehensive AI-Driven System for Video Interviews, Emotion Analysis, and Content Evaluation

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Major: AI

Project parts

Speech recognition

Recognizing emotions in spoken language.

Answer evaluation

Evaluating candidate answers for correctness.

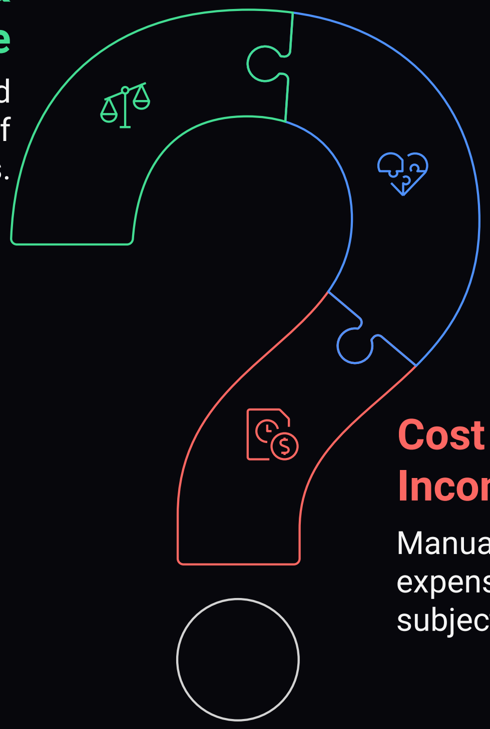
Report generation

Automatically generating reports based on data.

Why build an end-to-end AI interview tool?

Fairness & Scale

AI can reduce bias and handle large volumes of interviews.



Fragmented Solutions

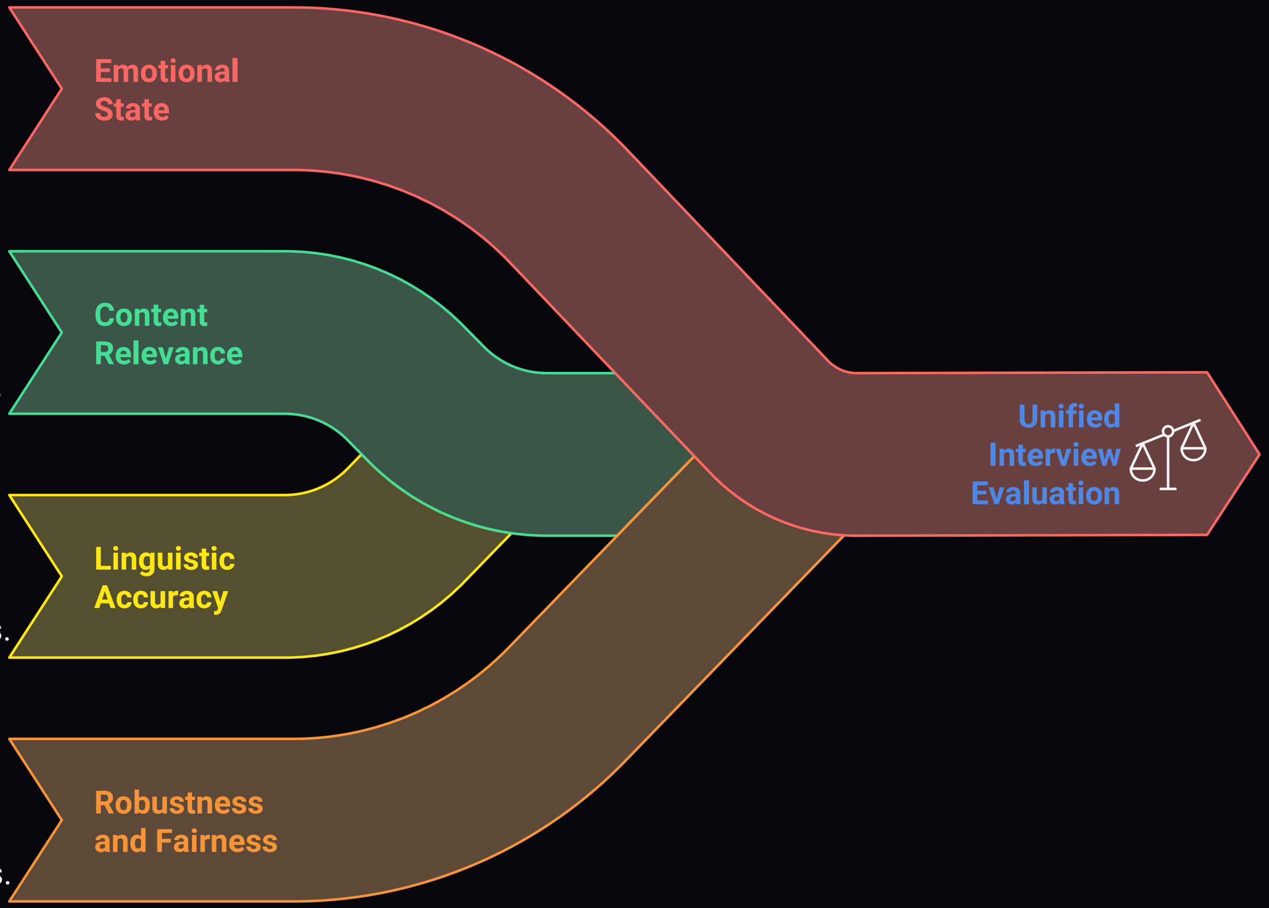
Existing solutions lack integration of key features.

Cost & Inconsistency

Manual interviews are expensive and prone to subjective biases.

Problem Statement

1. Analyzes emotional tone through speech-emotion recognition.
2. Evaluates how well answers address interview questions.
3. Assesses grammar and fluency in interview responses.
4. Ensures consistent scoring across multiple evaluations.



Research Questions

SER Accuracy

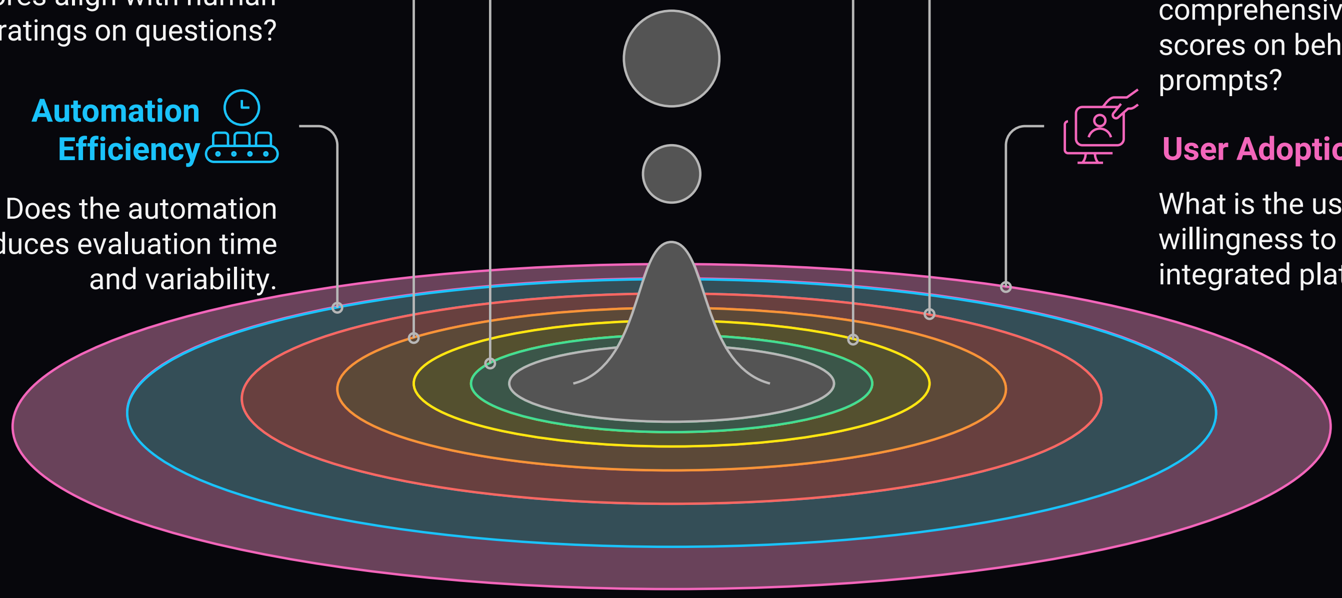
How accurately do the SER models classify unseen emotional speech?

AI Score Alignment

How closely do AI scores align with human ratings on questions?

Automation Efficiency

Does the automation reduces evaluation time and variability.



Data Augmentation Impact

Does augmenting Training data measurably improve generalization performance on unseen interview videos?

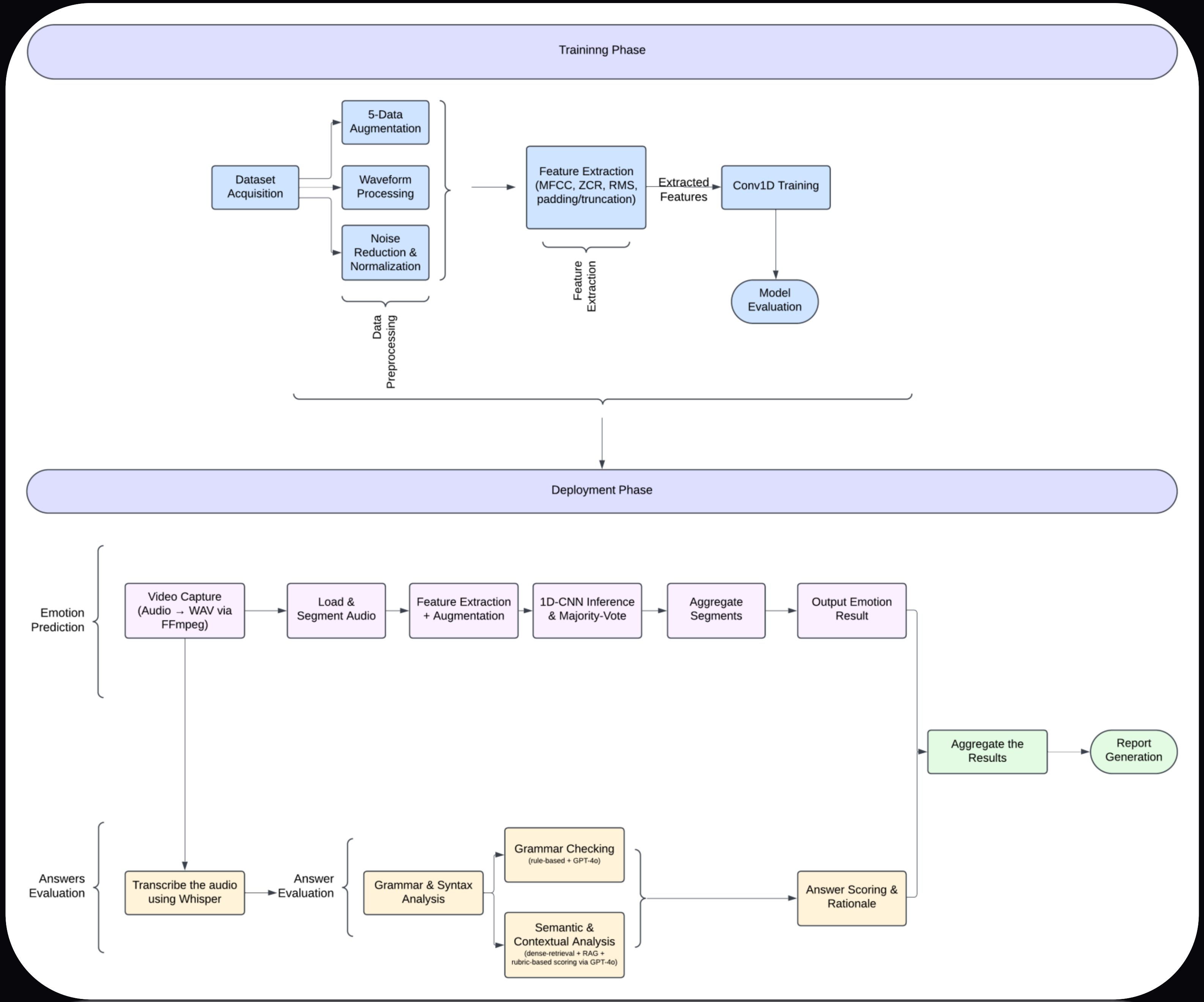
AI Score Fairness

How fair and comprehensive are AI scores on behavioral/HR prompts?

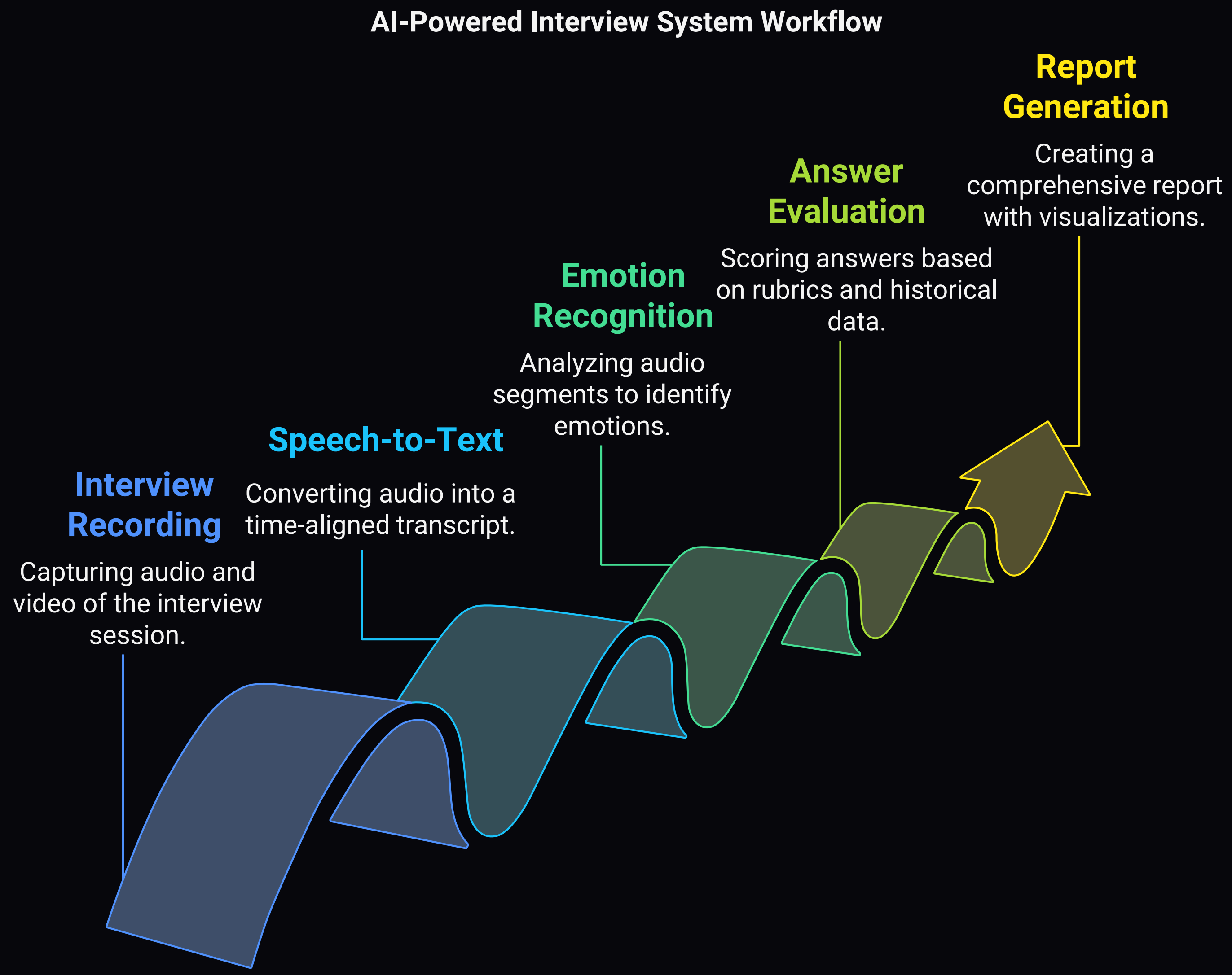
User Adoption

What is the user's willingness to adopt the integrated platform?

Methodology: End-to-End Pipeline



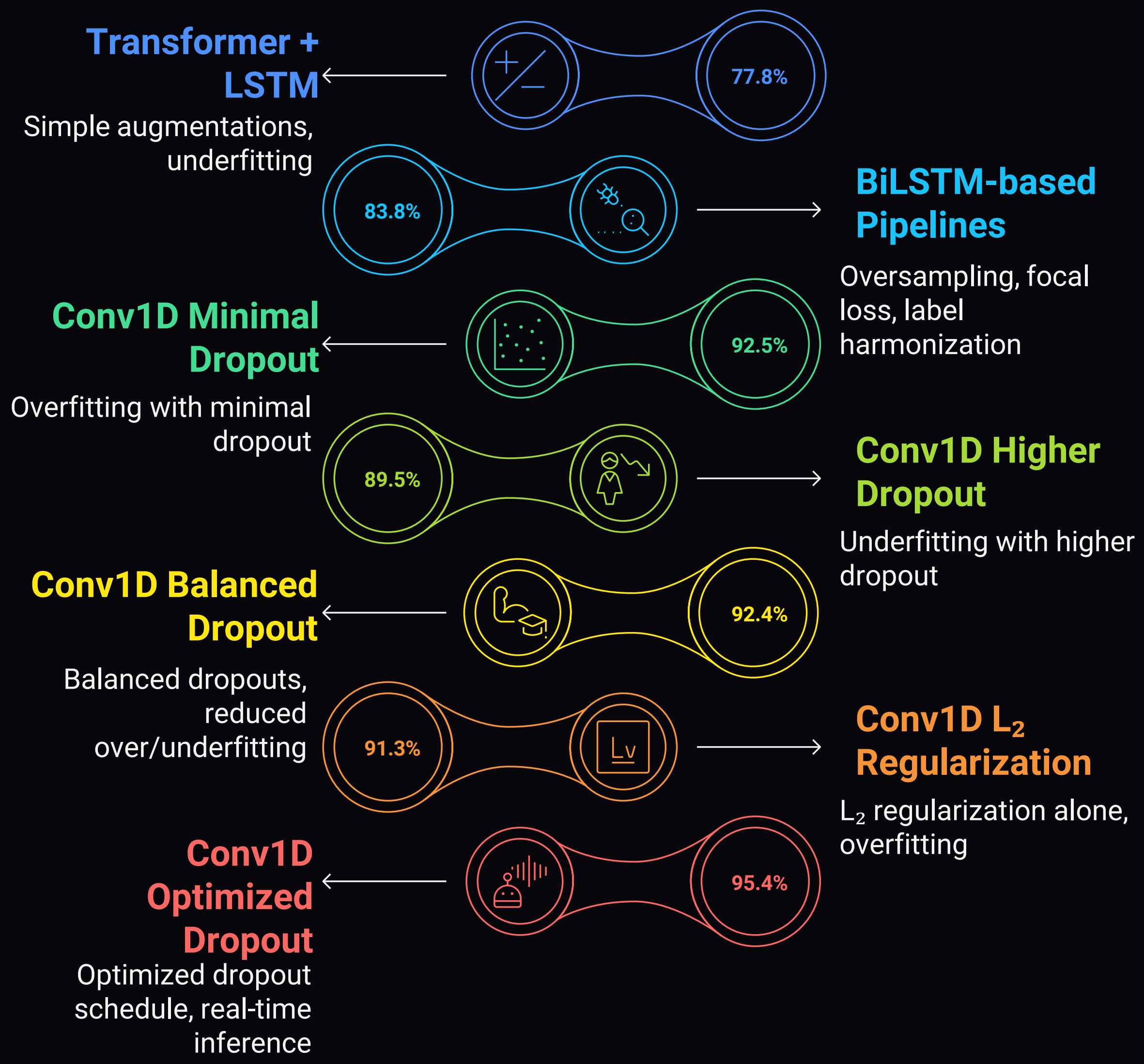
Methodology: End-to-End Pipeline



Speech Emotion Recognition

SER Model Selection Trials – 16 Trials

Performance of Different Model Architectures



Enhancing SER Model with Diverse Datasets

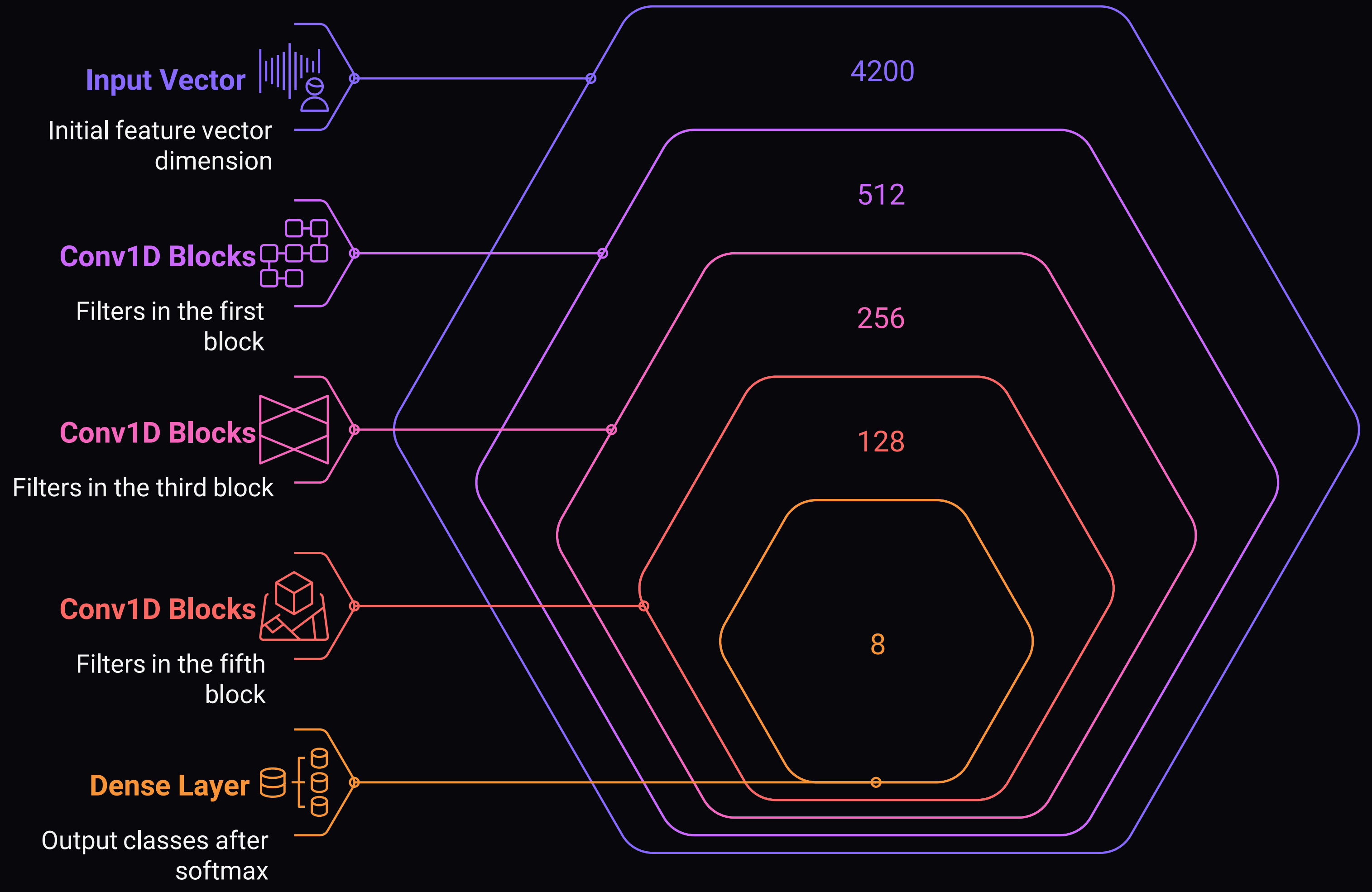
RAVDESS
Balanced emotions and controlled environment

CREMA-D
Large speaker pool and crowd-sourced labels

TESS
Age diversity with female speakers

SAVEE
Male speakers and spontaneous utterances

Audio Feature Vector Transformation



Dropout Rates in Conv1D Blocks

Block 1

Initial dropout rate for regularization

Block 2

Increased dropout for enhanced regularization

Block 3

No dropout applied in this block

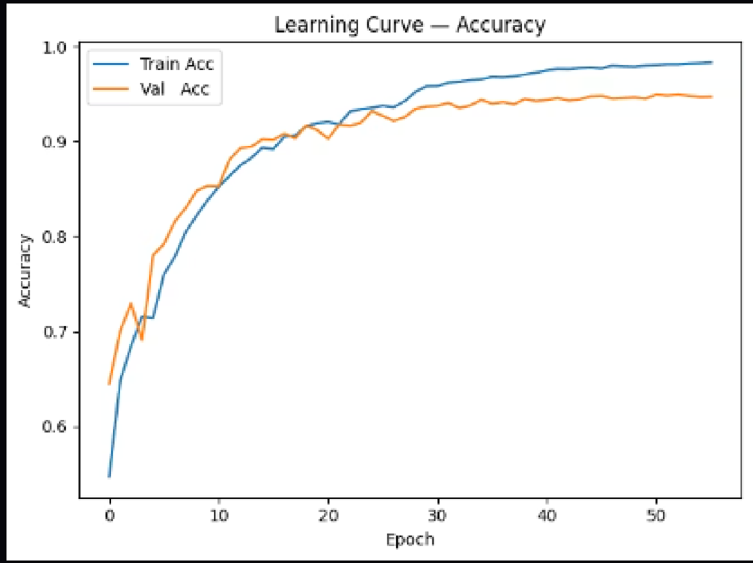
Block 4

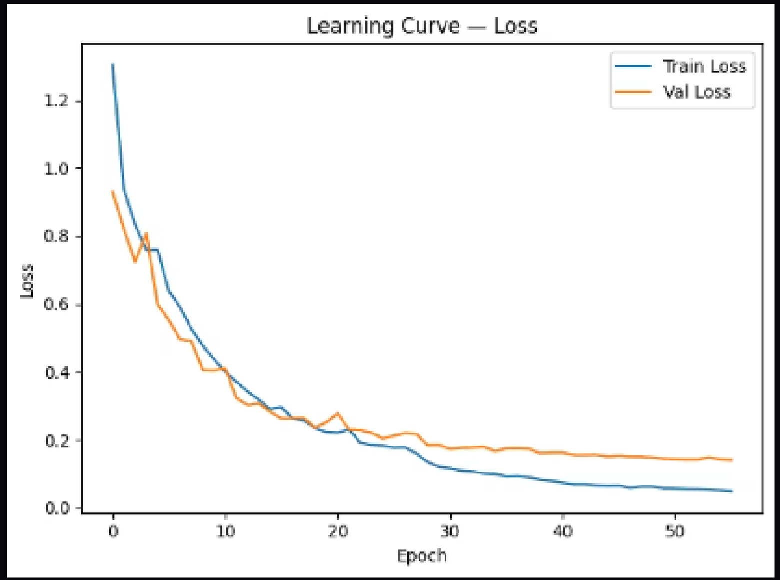
Dropout rate reintroduced for regularization

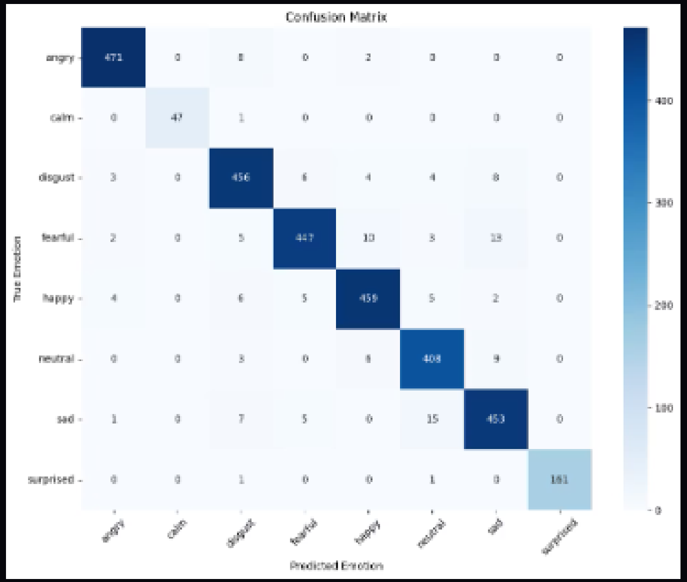
Block 5

Highest dropout rate for final regularization

SER Performance: Accuracy & Confusion Matrix





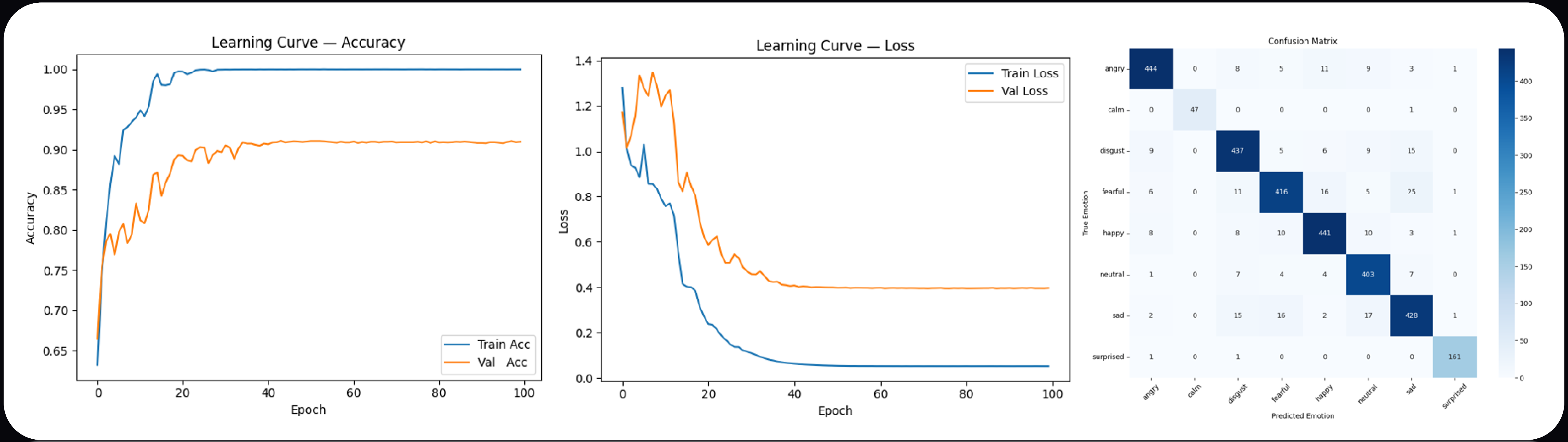


Train Accuracy:	99.98 % → near-perfect fit
Validation Accuracy:	94.93 %
Test Accuracy:	95.43 %
Key Finding:	Minimal gap between val/test confirms that overfitting has been effectively solved through progressive dropout, batch normalization, and delayed early-stopping

Overall Metrics

Macro-averaged F_1:	0.96
Overfitting addressed:	Regularization and callbacks ensured robust generalization
Supports	reliable emotion classification in AI-driven interview evaluation pipelines

Comparing to L2 Regularized Conv1D

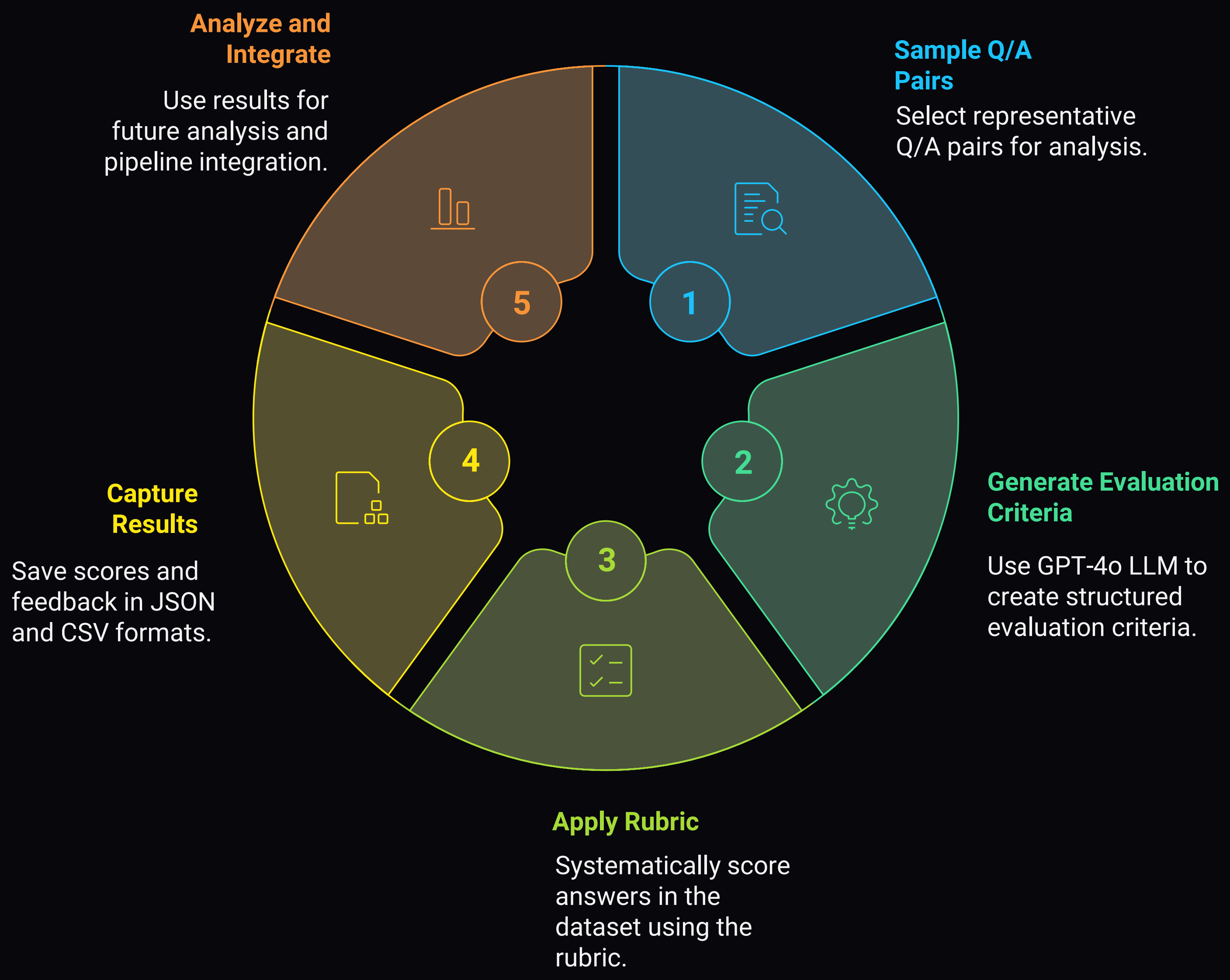


Candidate Answer Evaluation

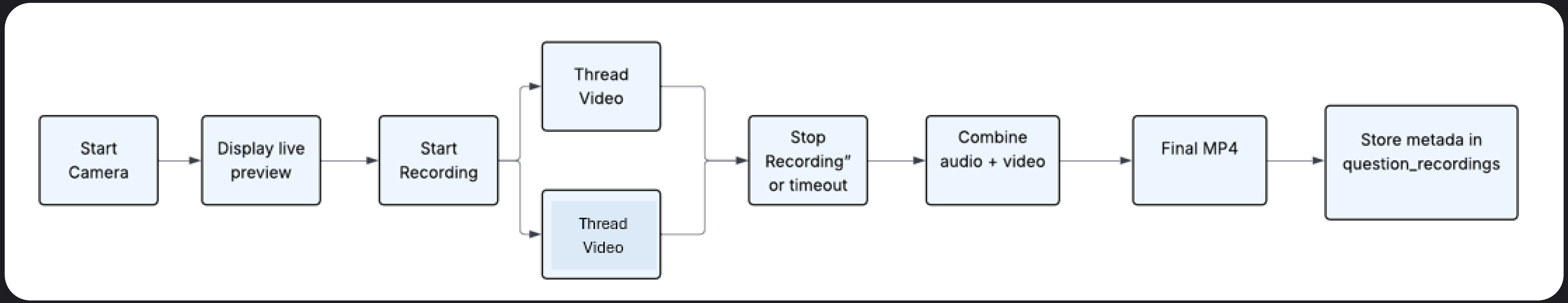
HR & Technical Datasets Preprocessing

Characteristic	Technical	HR
Initial Steps	ASCII normalization, whitespace collapsing	ASCII normalization, whitespace collapsing
Additional Step	None	Instruction-to-concrete-answer transformation using GPT-4o
Empty Answer Handling	Filtered out empty/placeholder answers	Flagged instructional answers for transformation
Markup Removal	HTML tags, Markdown artifacts, list bullets excised	HTML tags, Markdown artifacts, list bullets excised
Final Output	qa_preprocessed.csv	interview_best_answers_cleaned.csv

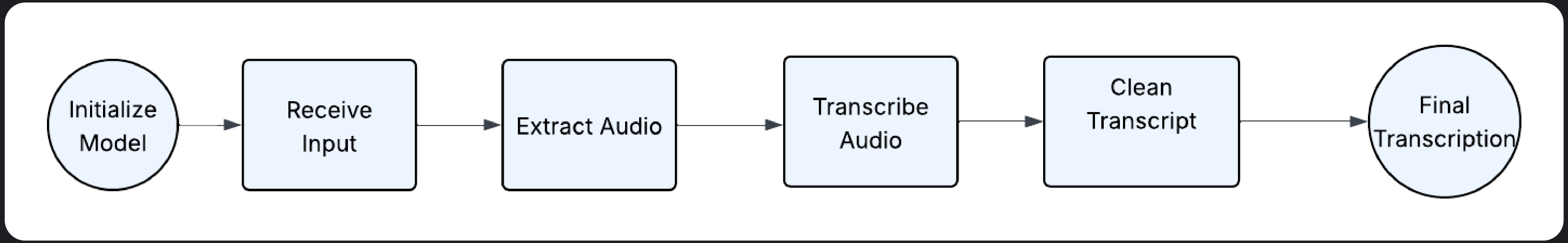
Rubric-Based Generation Cycle



Audio/Video Recording Workflow



Transcription with Whisper



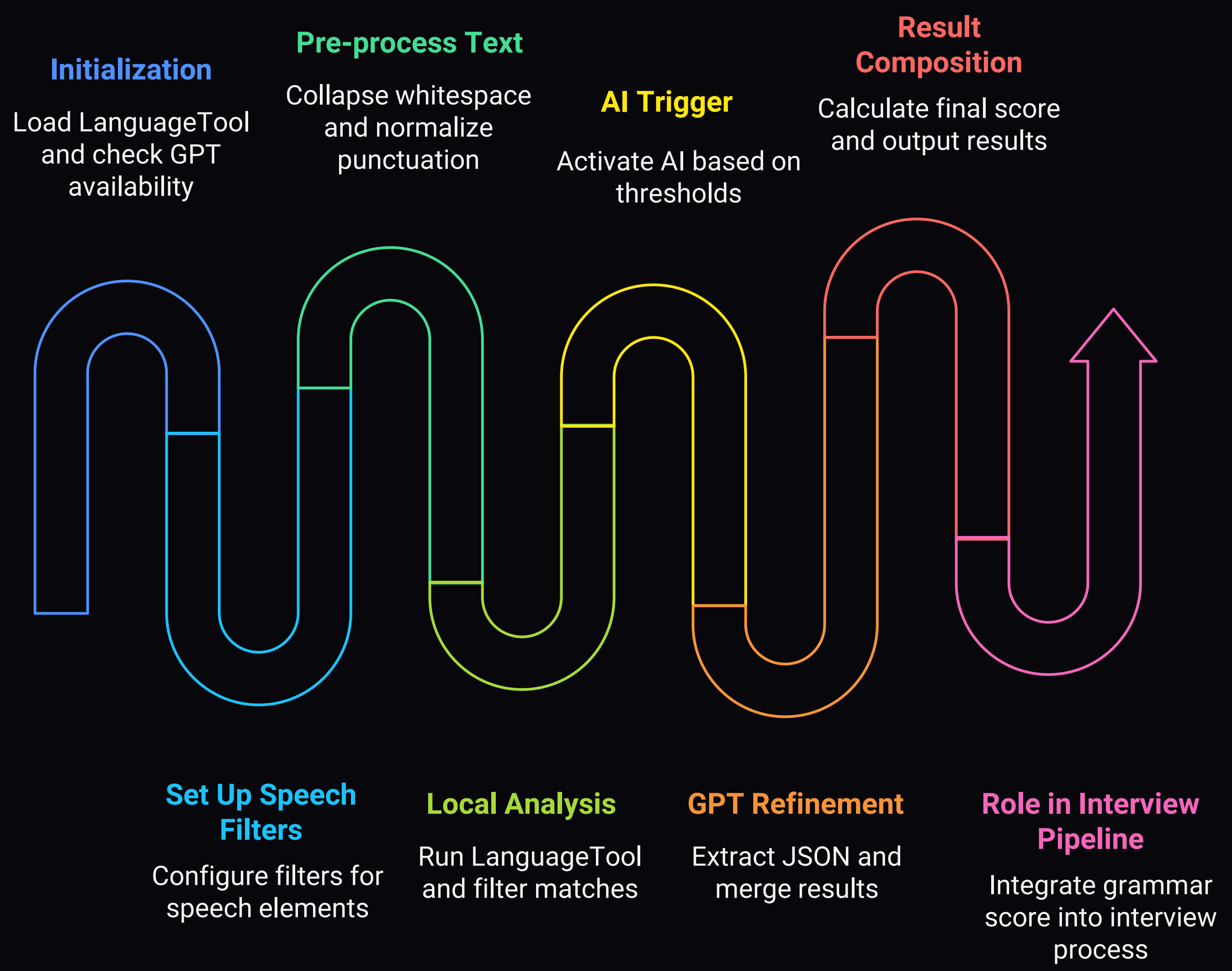
Score Integration Based on Retrieval Outcome

Outcome	Exact Match	Most Relevant Neighbors	No Match/Relevance
Old Score	Retrieve matched question's old score	Compute average old score	N/A
Combination Rule	If old score > 70: 70% old + 30% fresh; else: 100% fresh	30% average old + 70% fresh	100% fresh

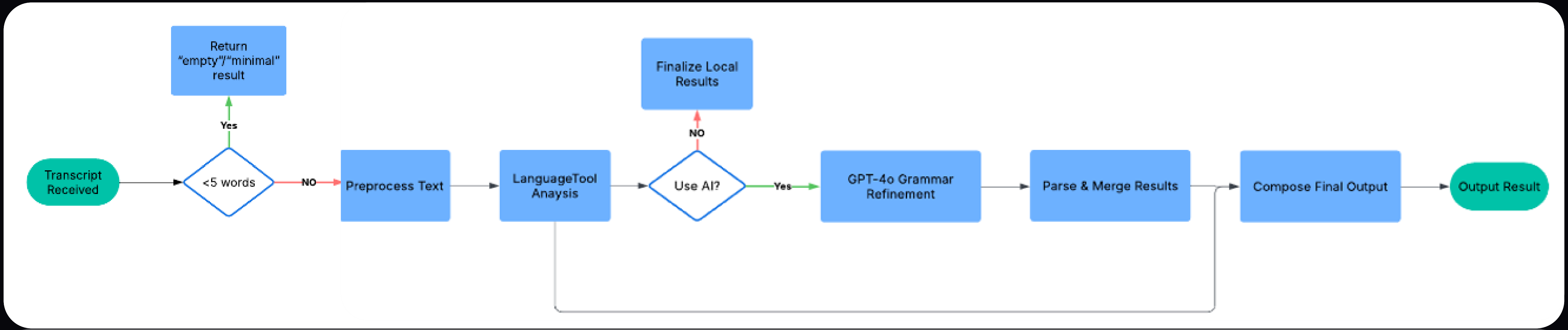
Enhancing GPT-4o Evaluation by RAG

Characteristic	RAG Module	GPT-4o Evaluation
Data Source	Real, high-quality exemplar answers	Model’s latent space
Hallucination Risk	Sharply reduces	Higher risk
Judgment Alignment	Aligns with domain-specific gold standards	May deviate from standards

Grammar Evaluation Process

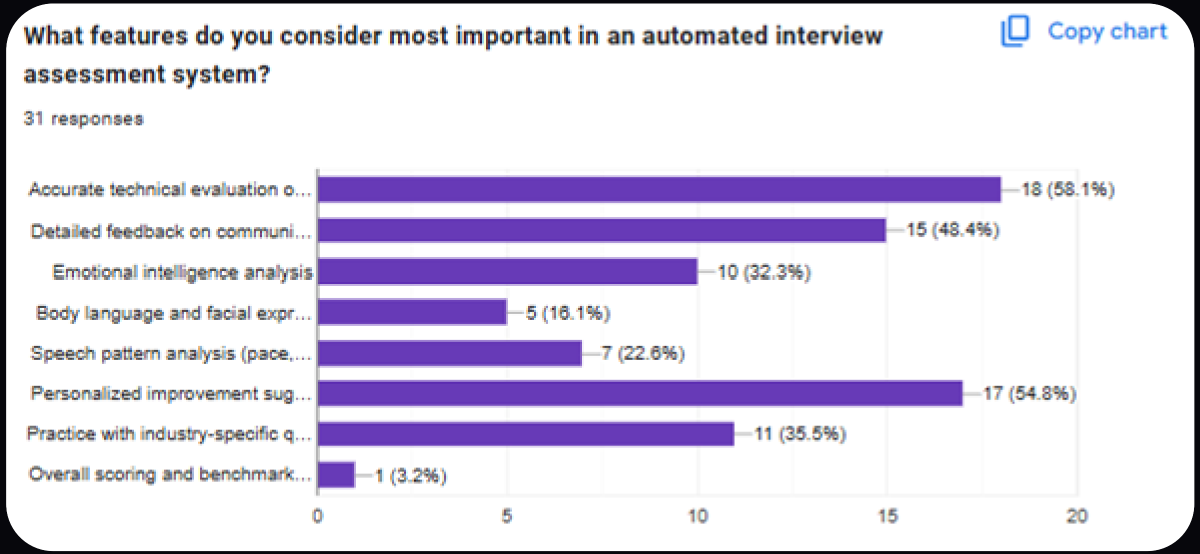


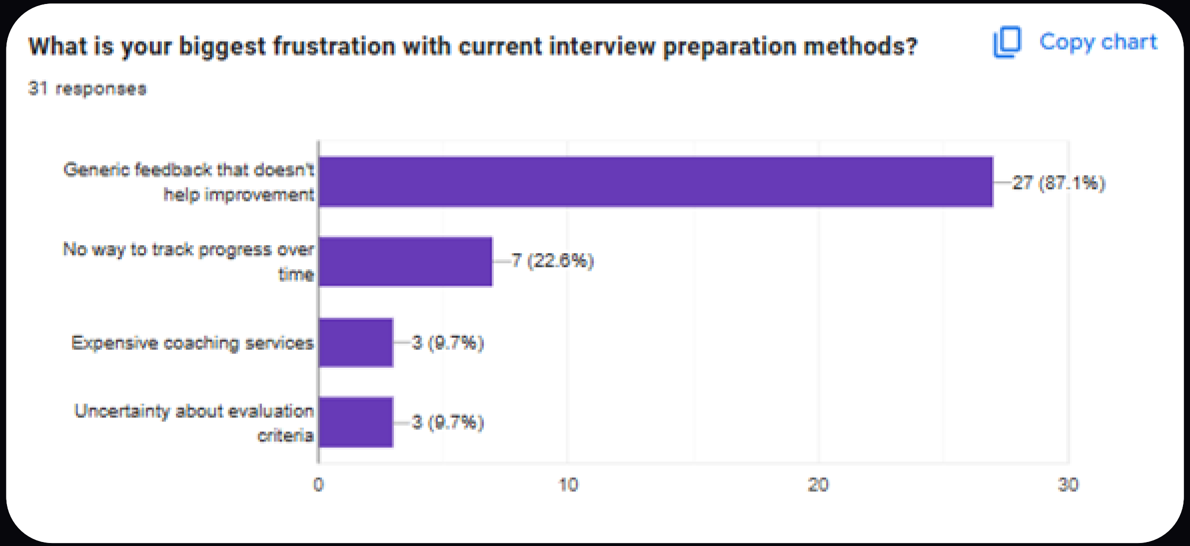
Grammar Evaluation Process



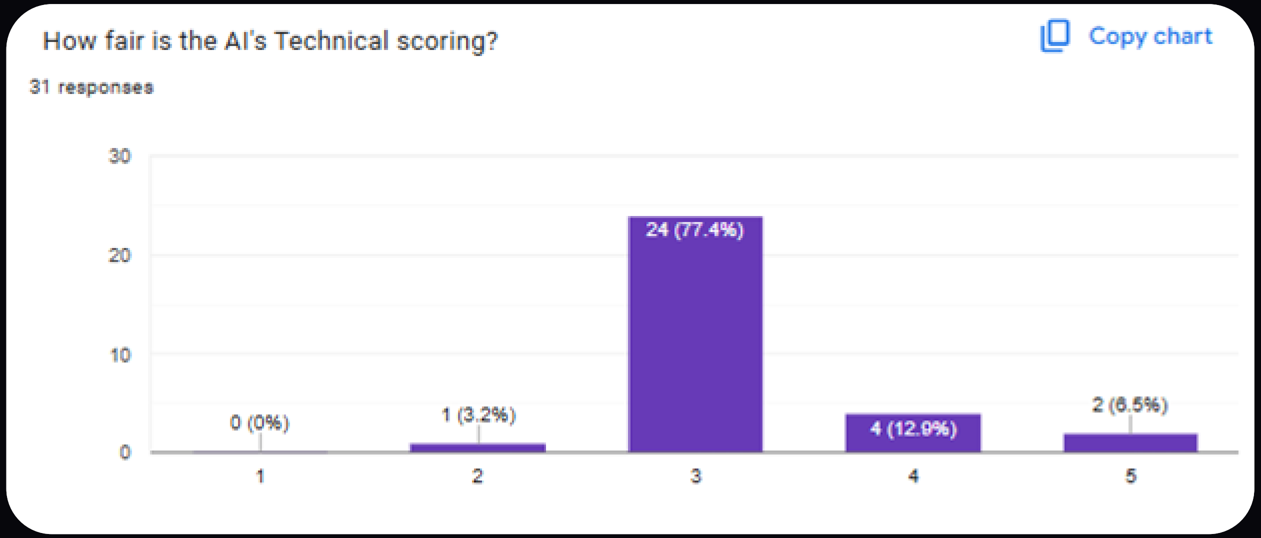
Human Evaluation Results

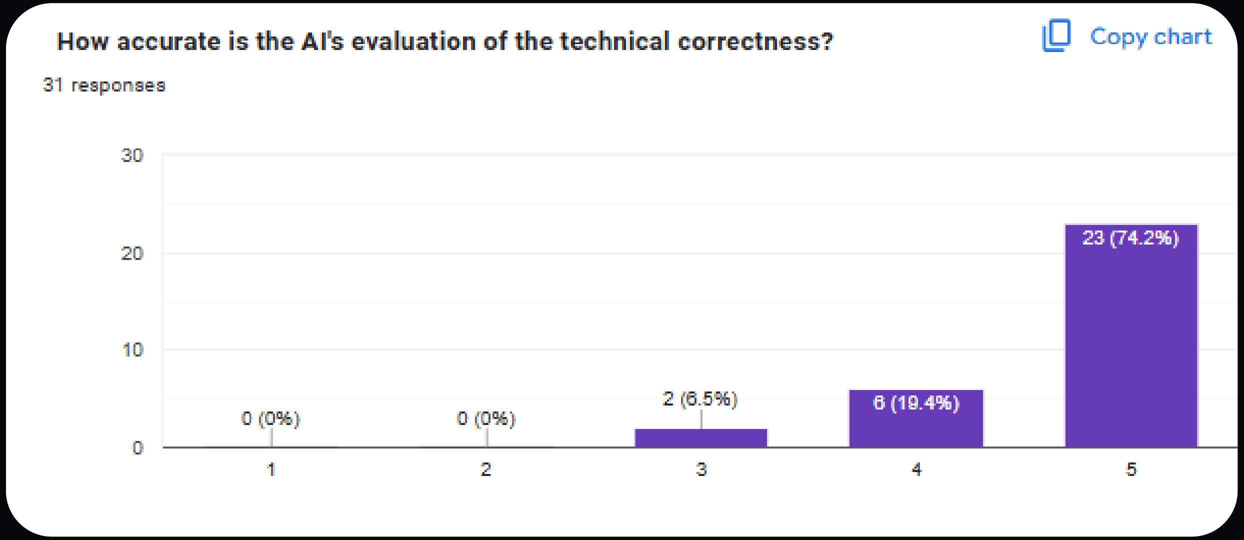
Participant Expectations for an Automated Interview System



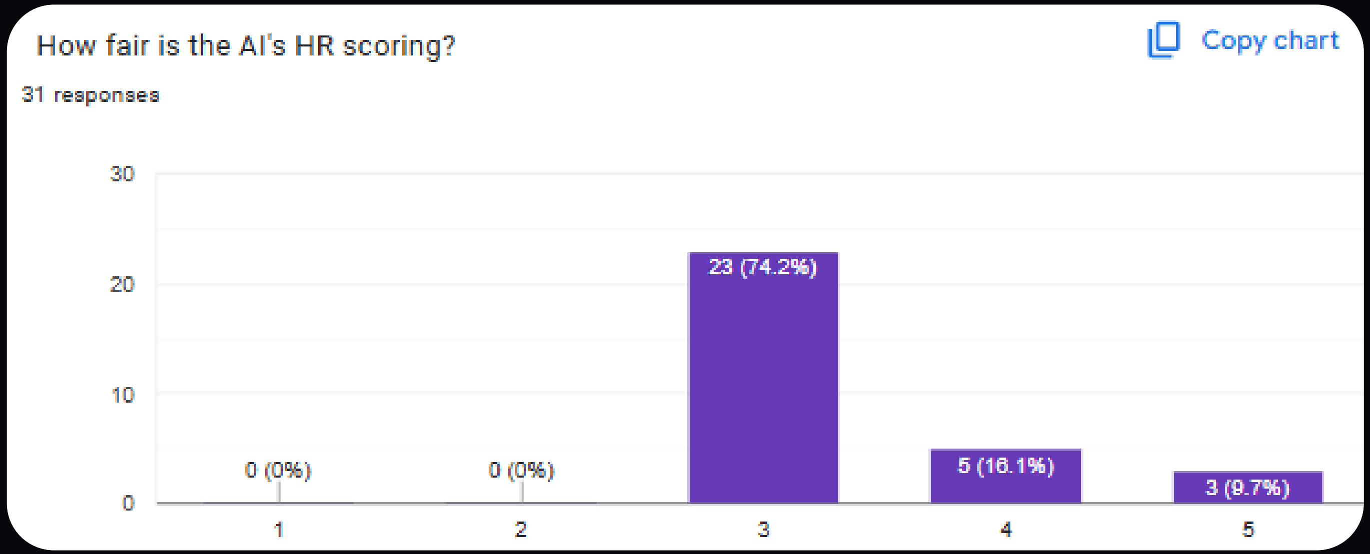


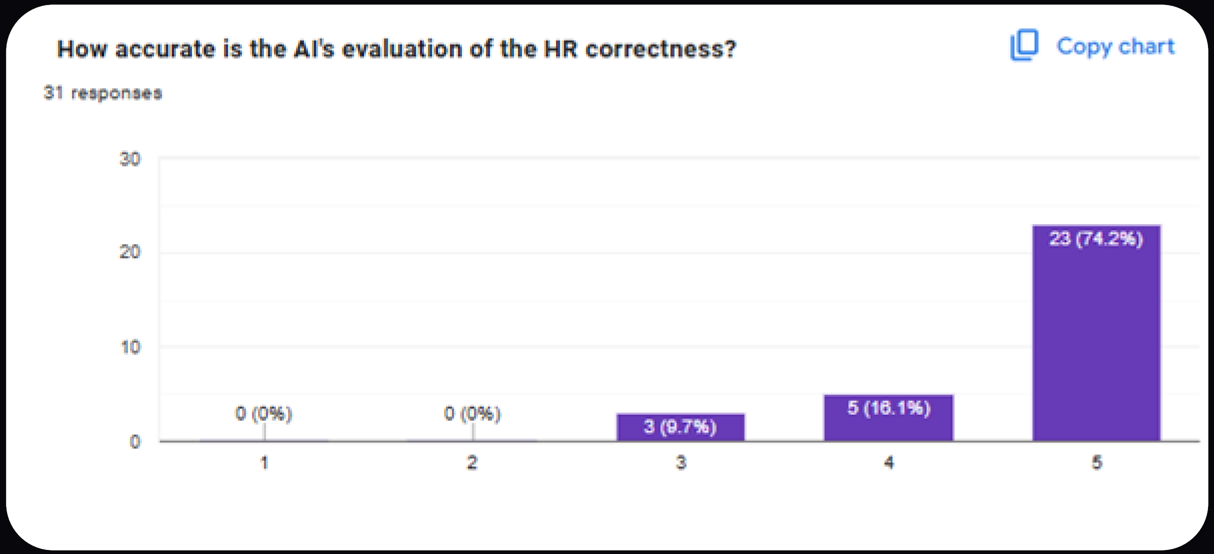
Technical Interview Question Evaluation



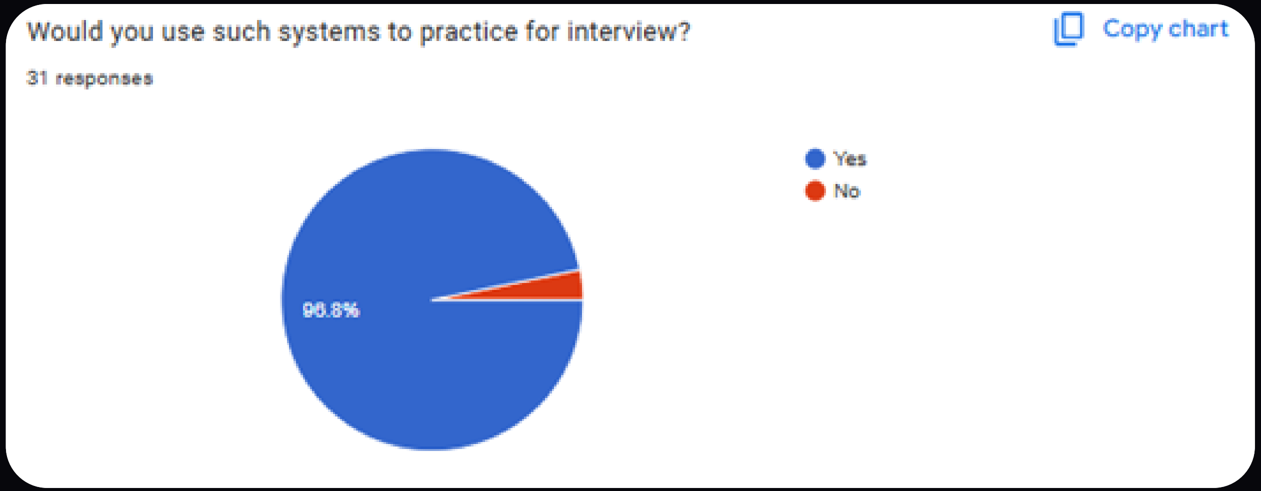


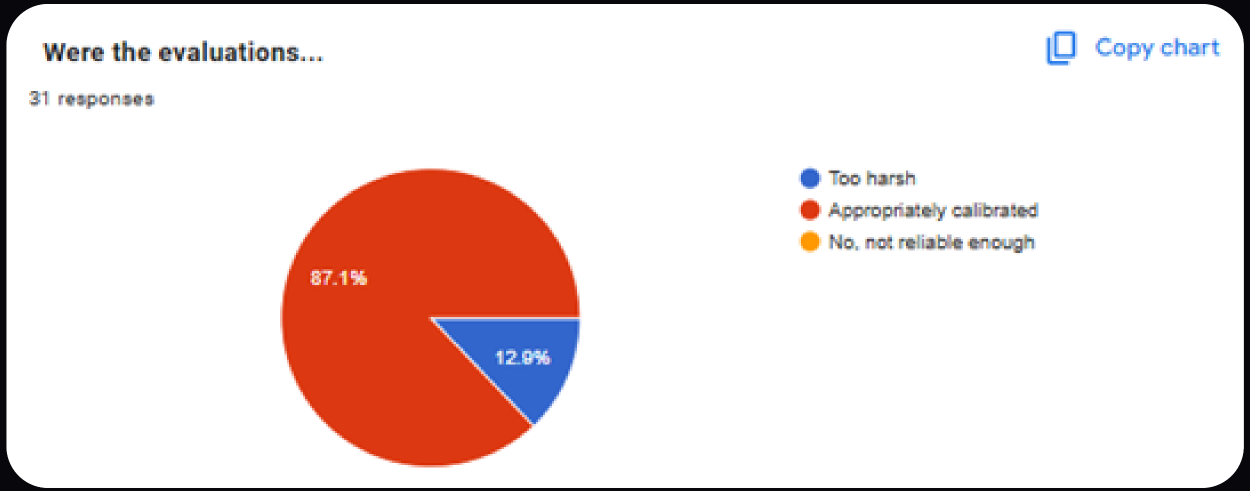
HR Interview Question Evaluation





Overall Assessment of LLM Evaluation Quality





Ethical Concerns

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Key Concerns

- **Privacy & Consent**
  - Audio/transcripts = personal data → explicit opt-in & clear usage disclosures
- **Bias & Fairness**
  - Accent/demographic gaps → risk of unequal performance
- **Transparency**
  - Opaque LLM decisions → need for explainable scores

Planned Mitigations

- **Privacy by Design**
  - End-to-end encryption, strict ACLs, auto-delete policies
- **Bias Monitoring**
  - Regular subgroup audits, diverse data augmentation, debiasing methods
- **Explainable Scoring**
  - Publish rubrics & weights, per-criterion rationales, confidence intervals, human-in-the-loop overrides
- **Governance & Compliance**
  - GDPR/CCPA alignment, Ethics Board oversight, continuous policy updates

Conclusion

Critical Analysis & Literature Comparison

SER Model Performance

- Our Conv1D Network

95.4 % accuracy (macro-F1 ≈ 0.96) on four heterogeneous English corpora

Light augmentations + optimized dropout (0.3→0.5) solved overfitting and boosted "calm" recall to 98 %

Compared to Prior Work

Liu et al. [1] & Wani et al. [2]: reported 77–86 % on similar English datasets

Issa et al. [3]: 71.6 % (RAVDESS), 86.1 % (EMO-DB), 95.7 % (trimmed EMO-DB)

Limitations: small, acted German speech ➔ poor real-world generalization

Answer-Evaluation Pipeline

Our Retrieval-Augmented Approach

Custom rubrics + FAISS anchors + fresh GPT-4o scoring

93 % technical & 90 % HR score agreement with human raters

96.8 % user adoption willingness

Compared to Static Rubric Methods

Traditional fixed rubrics lack adaptability to varied Q&A types

Our dynamic retrieval blending historical & fresh scores yields higher alignment and user trust

Conclusion: Research Questions Revisitation

1. **SER Effectiveness:** The final 1-D Conv consistently classifies unseen emotional speech with high accuracy, and optimized dropouts are shown to significantly improve generalization, especially on under-represented classes.
2. **LLM-Driven Answer Evaluation:** AI-generated rubric scores closely mirror expert human ratings on both technical and behavioral prompts, confirming that the retrieval-augmented, multi-pass evaluation reliably captures content correctness and nuance.
3. **Overall System Acceptance:** Integrating SER and LLM-based scoring into a unified pipeline substantially streamlines the interview review process—reducing evaluation effort and inter-rater variability—and most users report they would adopt the platform for both practice and formal screening.

References

[1] Z.-T. Liu, M.-T. Han, B.-H. Wu, and A. Rehman, "Speech emotion recognition based on convolutional neural network with attention-based bidirectional long short-term memory network and multi-task learning," *Applied Acoustics*, vol. 202, pp. 109178, Dec. 2022. [Online]. Available: https://doi.org/10.1016/j.apacoust.2022.109178.

[2] T. M. Wani, T. S. Gunawan, S. A. A. Qadri, M. Kartiwi, and E. Ambikairajah, "A comprehensive review of speech emotion recognition systems," *IEEE Access*, vol. 9, pp. 47795–47813, 2021. [Online]. Available: https://doi.org/10.1109/ACCESS.2021.3068045.

[3] D. Issa, M. F. Demirci, and A. Yazici, "Speech emotion recognition with deep convolutional neural networks," *Biomedical Signal Processing and Control*, vol. 59, 2020, pp. 101894. [Online]. Available: https://doi.org/10.1016/j.bspc.2020.101894.

Thank You !