

AI-Driven Survivor Journey Mapping for TAPS: Automating Grief Stage Classification

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ABSTRACT

We developed an AI, machine learning-powered solution to automate the classification of grief stages in survey responses for the Tragedy Assistance Program for Survivors (TAPS), which supports families of fallen military personnel. TAPS serves an average of 26 new survivors daily, manually analyzing survey data to assess each survivor's grief stage—a time-consuming process that limits scalability (TAPS, 2023).

Leveraging machine learning and natural language processing (NLP), our model classifies grief stages with over 90% accuracy, enabling TAPS to make data-informed decisions and deliver stage-appropriate resources more effectively. This project addresses the unique challenges of supporting military families, where grief is often compounded by trauma, loss of community, and identity challenges. By automating this process, the system improves the consistency and reliability of grief stage classification, freeing staff to focus on direct survivor care and outreach.

Conducted as part of the Data4Good competition, this project placed in the top 5 for Region 2, showcasing its innovation and social impact. Our findings demonstrate the potential of AI to enhance scalability and resource allocation, contributing to improved support services for grieving military families.

BUSINESS PROBLEM

The Tragedy Assistance Program for Survivors (TAPS) plays a critical role in helping military families navigate the grief journey after the loss of a loved one. However, the current manual approach to assessing grief stages from survey responses is labor-intensive and leads to significant delays in providing essential support. These delays hinder timely intervention, which is crucial for improving mental health outcomes and emotional recovery.

Prolonged grief disorder impacts approximately 10% of those who experience loss, often leading to severe consequences such as depression, anxiety, and diminished well-being (The New York Times, 2023). For military families, the unique stressors compound these risks. Addressing this challenge, organizations implementing AI-driven process automation achieve up to 60% time savings, freeing staff to focus on direct care rather than administrative tasks (Brookings Institution, 2022). This project leverages machine learning and NLP to automate grief stage classification, reducing processing times by up to 60%. By doing so, TAPS can provide scalable, personalized support precisely when it is needed most, aligning with its mission to foster healing and resilience in grieving families.

TAPS Journey Process

- Immediate Grief, Shock & Emotion**
Overwhelmed by loss, isolation, and trauma, the family struggles with responsibilities, leaving the surviving child feeling disconnected and unguided.
- Navigating Family Relationships**
Family members experience tension and limited support, each at different stages of grief and recognizing diverse expressions of their grief between family members.
- Learning to Process Grief**
Beginning to process grief, the surviving child seeks validation, guidance, and connection with peers to normalize feelings.
- Moments That Matter**
The family experiences renewed grief during special events like anniversaries, holidays, and milestones like school or sports achievements.
- Feeling Immersed, Connected & Seen**
The family begins to reconnect with purpose, integrating the loss positively and finding support in a broader community, realizing they are not alone.
- New Growth & Purpose**
The family reaches a healthier place in their grief, ready to support others by engaging in mentorship, volunteering, or community activities with TAPS.

ANALYTICS PROBLEM FRAMING

Problem Definition
Develop an NLP-based model to classify open-ended survey responses from TAPS participants into specific stages of grief, enabling TAPS to provide timely, stage-appropriate support to military families.

Key Assumptions
Each grief stage has distinct linguistic patterns that can be identified through NLP. Survey responses contain enough context for accurate classification. Automated classification will reduce response times and improve support quality.

Success Metrics
Classification Accuracy: Model achieves 85%+ accuracy in stage classification.
Reduction in Manual Effort: Measure reduction in time staff spend on manual classification.
Survivor Satisfaction: Positive feedback on the relevance and responsiveness of support.

Justification
Manual classification is inefficient and slows access to vital resources. Automating this process with AI enables scalable, immediate support, aligning with TAPS' mission to assist grieving families when they need it most. AI-driven automation has shown potential to reduce processing times by up to 60% (Brookings, 2022), which is critical in addressing the emotional needs of survivors quickly and effectively.

RESEARCH QUESTIONS

- How accurately can natural language processing (NLP) and machine learning models classify survey responses into predefined grief stages in the TAPS Survivor Journey Map?
- Can automating the classification of grief stages in survey responses significantly reduce response time, thereby improving the timeliness and personalization of support provided by TAPS to military families.

DATA

Data Sources

Training Set
Contains survey responses labeled by grief stage. It includes multiple-choice responses and open-ended text responses along with the target label.

Test Set
Contains survey responses without target labels to evaluate model predictions.

Sample Submission
Sample with expected format for model, with unique identifiers and predicted grief stage labels.

Data Preprocessing

Handling Missing Values: Several questions have missing values, especially in the open-ended responses which were handled by either imputing or discarding them, depending on the missingness pattern.

Text Cleaning: Open-ended responses require preprocessing, including removing punctuation, lowercasing, and tokenizing, to prepare for NLP analysis.

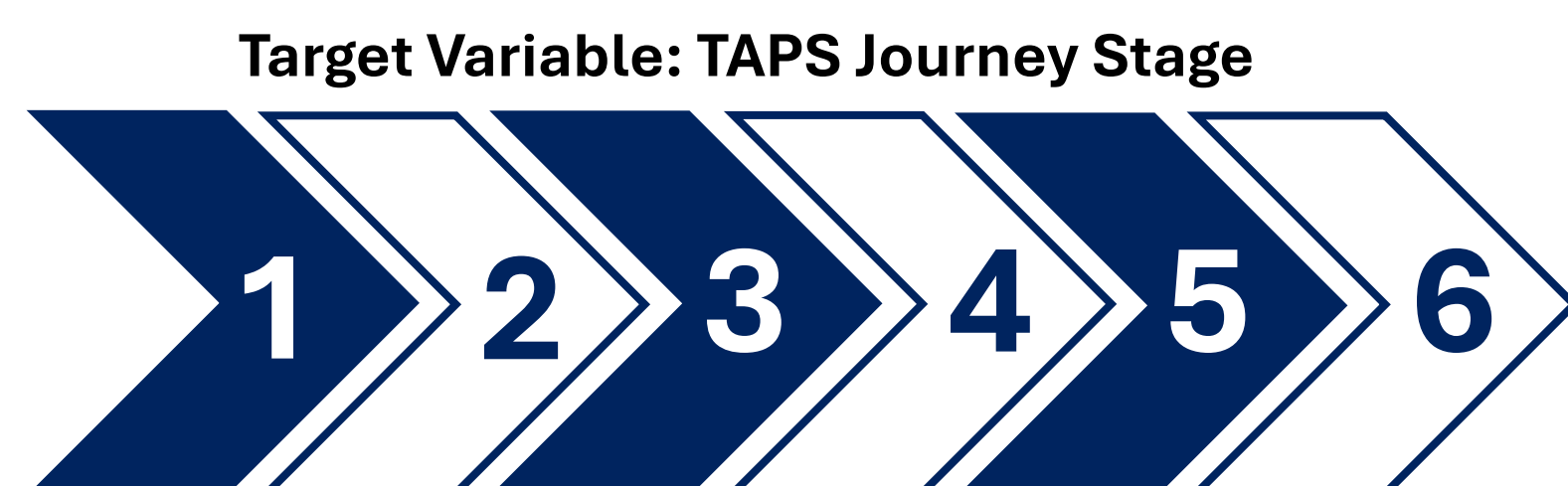
Feature Scaling: Standardize numeric responses (q1-q20) if needed for model compatibility.

Encoding Labels: Convert target labels into numeric or categorical format suitable for supervised learning.

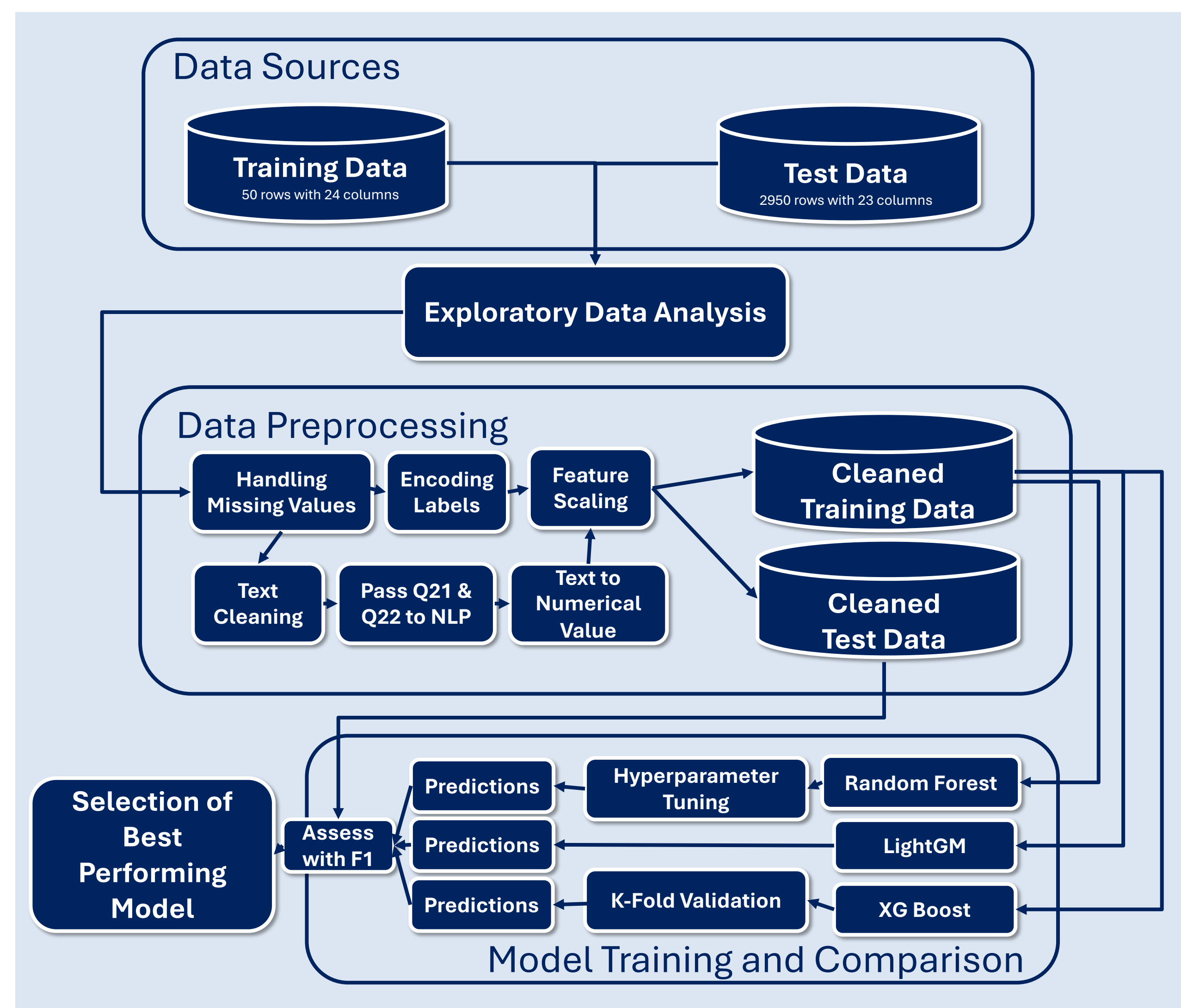
Notable Data Relationships

Multiple Choice and Open-Ended Correlation: The multiple-choice responses (q1-q20) might correlate with open-ended responses, providing context to strengthen the model's predictive power.

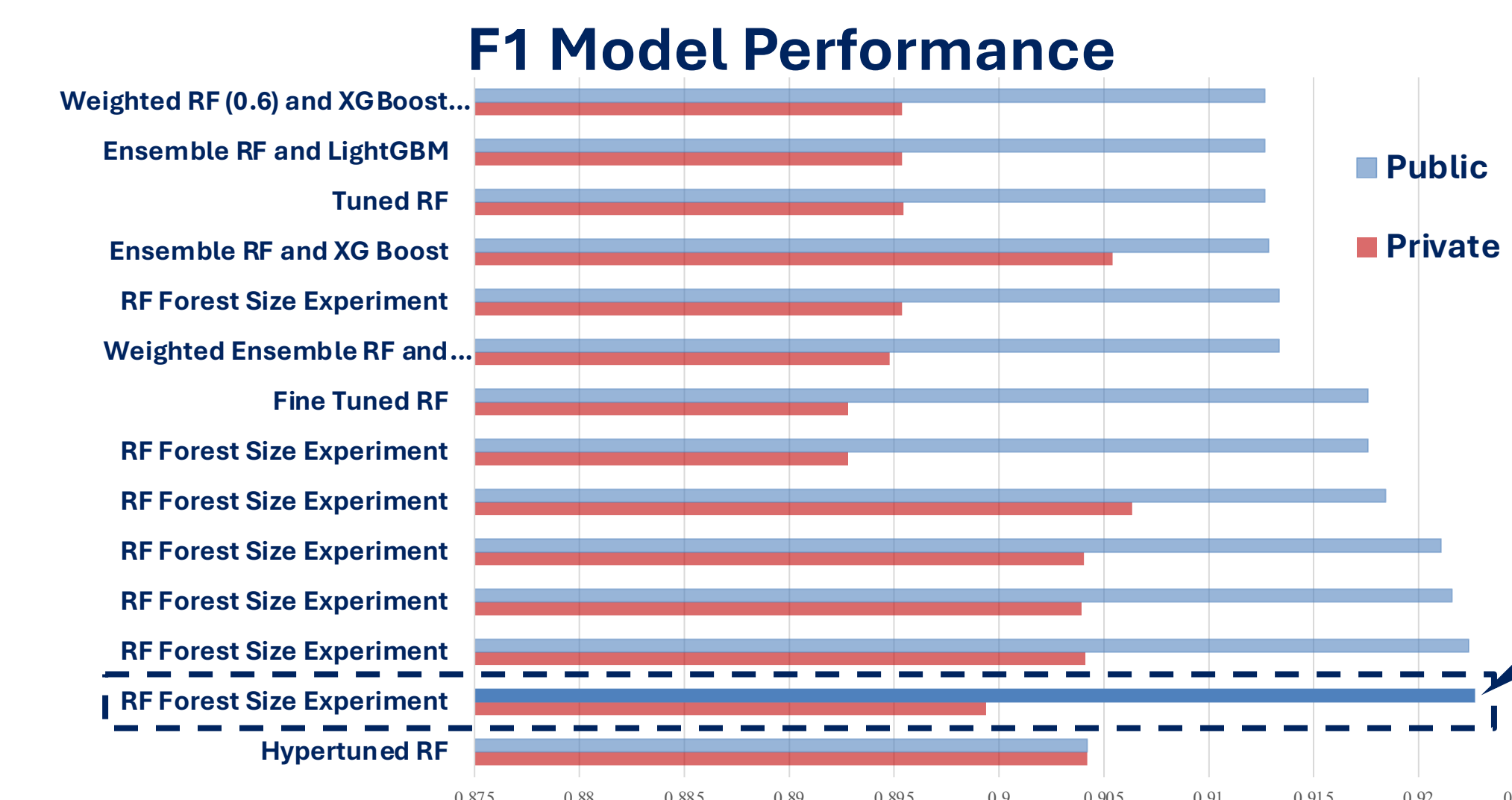
Linguistic Patterns and Grief Stages: Text responses likely contain distinct language indicative of specific grief stages, enabling NLP-based classification.



METHODOLOGY



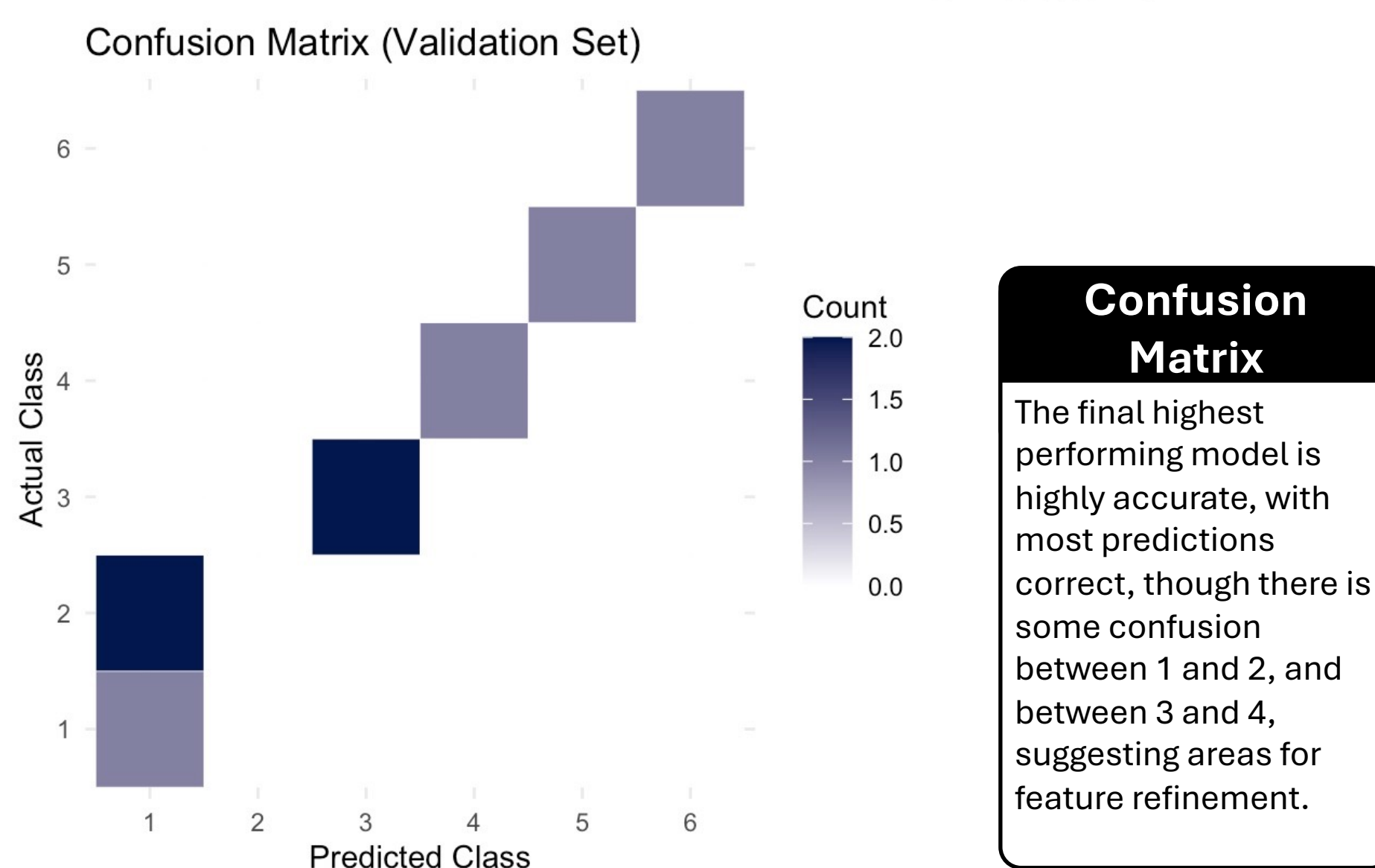
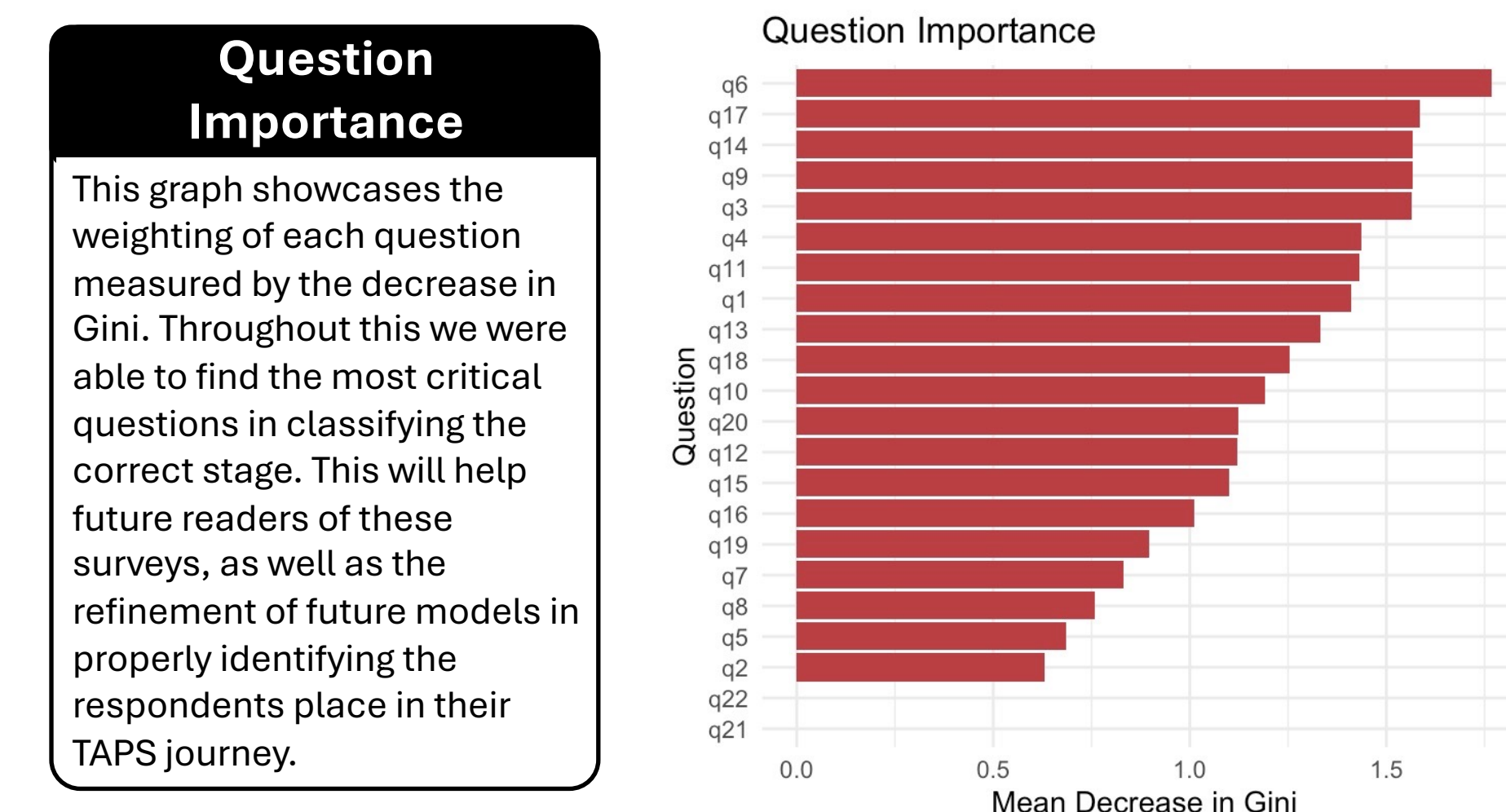
MODEL BUILDING & EVALUATION



Key Takeaways

Random Forest proved to be the most effective model of the ones test. The public and private score were designated based on what would show on the Kaggle leaderboard. However, the RF model still proved best in both.

MODEL BUILDING & EVALUATION



CONCLUSIONS

- Insights**
Developing an AI, machine learning-powered solution to streamline the classification of grief stages in survey responses for TAPS is important because delays can hinder emotional recovery. Our findings demonstrate how AI can make a difference in the lives of those coping with loss.
- Outcomes**
- The Random Forest was able to predict intermittent demand with a 15% MAPE, which was 5% better than the currently used model.
 - All our ML models performed on average 4% better than Croston's method.
- Hurdles**
Throughout our research experiments, we were dealt with challenges due to the small limited training set. However, the insights discovered indicate further room for research.