

Automated Behavioral Coding to Enhance the Effectiveness of Motivational Interviewing in a Chat-Based Suicide Prevention Helpline

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Outline



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- Research motivation
- Research goals



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Classification performance

- AI models
- Explainability



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Background

Motivational Interviewing

What is MI?

Motivational interviewing is a collaborative, goal-oriented conversation style with special attention to change language.

It is designed to enhance personal motivation and commitment to a particular goal by eliciting and exploring one's own reasons for change in an atmosphere of acceptance and compassion.

Miller & Rollnick (2013)





Research motivation

Practical situation

- MI is a challenging skill to learn and requires substantial expertise to apply effectively.
- Counselors at 113 applied MI techniques consistently during chat conversations but could not strategically deploy MI techniques to elicit enough change talk from clients to change their behavior intrinsically (Janssen et al., 2022).
- By increasing their behavior awareness, counselors can significantly reduce cognitive effort and reflect on MI insights.





Research goals

Goals

- 1) Investigate the performance of AI models in classifying MI behavior.
- 2) Investigate the feasibility of using these models in helplines as an automated support tool for counselors in clinical practice.



Contributions

- Combining AI and MI focusing on suicide prevention
- Support crisis chat counselors in their practical challenges
- We describe our AI approach in detail following the best AI practices



Methodology

Data



- 17 codes for counselor messages
- 4 codes for client messages
- 2 codes for **MI-consistent / MI-inconsistent** counselor language
- 2 codes for evocative / non-evocative counselor language







Textual information



5850 features in total



Language insights





Temporal patterns

- Using Closed Questions, Non-Evocative language and Negative Reflections lead to Sustain Talk by clients.
- Using Positive Open Questions and Evocative language lead to Change Talk by clients.



Classification performance

AI algorithms

Machine learning

- Decision Tree
- K-nearest neighbours
- Random Forest
- SVM

Explainability: High

Transfer learning BERT (Devlin et al., 2018) by Google

- Captures **context** of words
- Pre-trained on millions on messages

Explainability: Medium





Classification performance



Note. The standard deviation (SD) for the results yields 0.015 for counselor behavior and 0.013 for client behavior. Confidence intervals for the results are given by performance value $\pm 2 \times SD$.

Model comparison

- All models significantly performed above the baseline.
- **BERTje** significantly outperformed the machine learning models.





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Classification performance (BERTje)

Counselor behavior

Fine-grained predictions Accuracy = 0.72, Kappa = 0.69 AUC range: 0.89 – 0.99

True label

MI-congruency Accuracy = 0.87, Kappa = 0.65 AUC = 0.92

Evocative language

Accuracy = 0.90, Kappa = 0.65 AUC = 0.92

Client behavior

Fine-grained predictions Accuracy = 0.70, Kappa = 0.50 AUC range: 0.81 – 0.99

| | contrasion matrix | | | | | | | | | | | | | | | | |
|---------------------------------|------------------------------|---------------------------------|--------------|-----------------|----------------|--------------------------|---------------|--------------------------|---------------------|---------------------|---------------------|---------------------------|----------------|-----------------|----------------------|-----------------|---------------|
| Advise with Permission (AWP) | 8 | 2 | 1 | 2 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 2 | 0 | 1 | 2 | 0 |
| Advise without Permission (ADW) | 1 | 9 | 1 | 4 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 2 |
| Affirm (Aff) | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 |
| Closed Question | 0 | 0 | 0 | 130 | 0 | 0 | 0 | 0 | 6 | 1 | 4 | 2 | 0 | 2 | 0 | 0 | 0 |
| Confront (Con) | 0 | 2 | 0 | 3 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 3 | 1 | 0 | 4 |
| Emphasize Control (Econ) | 0 | 1 | 0 | 4 | 0 | 2 | 0 | 1 | 2 | 0 | 1 | 2 | 0 | 0 | 0 | 1 | 1 |
| Filler (Fill) | 0 | 0 | 3 | 0 | 0 | 0 | 33 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 1 | 3 |
| General Information (GI) | 1 | 2 | 0 | 0 | 0 | 0 | 0 | 26 | 0 | 0 | 0 | 0 | 7 | 4 | 1 | 0 | 4 |
| Open Question (OQ+) | 0 | 1 | 0 | 8 | 0 | 1 | 0 | 0 | 51 | 2 | 7 | 0 | 1 | 0 | 0 | 0 | 0 |
| Open Question (OQ-) | 0 | 0 | 0 | 3 | 0 | 0 | 1 | 0 | 8 | 41 | 6 | 1 | 0 | 0 | 1 | 0 | 0 |
| Open Question (OQ0) | 0 | 0 | 0 | 6 | 0 | 1 | 0 | 0 | 14 | 9 | 64 | 1 | 1 | 0 | 0 | 0 | 0 |
| Permission seeking (Perm) | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 1 | 1 | 0 | 2 | 16 | 0 | 0 | 0 | 0 | 0 |
| Reflection (+) | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 11 | 1 | 1 | 2 |
| Reflection (0-) | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 8 | 88 | 1 | 1 | 4 |
| Self-Disclose (Sdis) | 0 | 0 | 1 | 0 | 1 | 0 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 3 | 3 |
| Structure (Str) | 0 | 1 | 2 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 1 | 3 | 5 | 2 | 70 | 0 |
| Support (Sup) | 0 | 1 | 1 | 1 | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 0 | 1 | 5 | 3 | 1 | 39 |
| | Advise with Permission (AWP) | Advise without Permission (ADW) | Affirm (Aff) | Closed Question | Confront (Con) | Emphasize Control (Econ) | Filler (Fill) | General Information (GI) | open Question (0Q+) | apen Question (OQ-) | Open Question (OQ0) | Permission seeking (Perm) | Reflection (+) | Reflection (0-) | Self-Disclose (Sdis) | Structure (Str) | Support (Sup) |

confusion matrix



Explainability



0.0 2.5 5.0 7.5 10.0 12.5 15.0 17.5 20.0 mean(|SHAP value|) (average impact on model output magnitude)



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Conclusions

Answers to the research questions



This study demonstrated the potential of AI models, particularly the transformer model BERTje, in classifying MI behavior in online mental health helplines.



Although the lower performance of the ML models, their high explainability adds value for gaining a deeper understanding of language use concerning specific MI behaviors.



The interpretable model predictions discerned client change- and sustain talk, counselor affirmations, and reflection types - the effective ingredients of MI - facilitating valuable counselor feedback.



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Implications for clinical practice

| Leveraging AI Models for Clinical Support | Evaluating the Effectiveness of AI Models | Next Steps to Take | Future Directions | | | |
|---|---|---|-----------------------------|--|--|--|
| Generalizable | Conduct pilot studies or RCT's analyzing changes in | Collect data. | Simulation tool. | | | |
| Integrate AI models into chat- | conversation outcomes over | Connect with other clinicians | Evaluate the performance of | | | |
| based counseling platforms. | time. | and researchers in the field. | these models on larger | | | |
| Offer post-session feedback Pr and training to counselors. | actical and scalable solution MI proficiency of coun | datasets. A classification model must become sensitive to the | | | | |
| Use AI models to monitor and | Counselors could provide | | processes of MI. | | | |
| evaluate the qualit counseling services he | Apply the methods used in this study to other languages | | | | | |
| Reduce the <i>time-to-</i> | | | and institutions. | | | |
| proficiency. | | | | | | |



Take-aways

- 1. Al is there to support you
- 2. Broader impact than just suicide prevention

The Impact of Artificial Intelligence



DEPARTMENT OF MATHEMATICS

Thanks for your attention! m.j.pellemans@vu.nl





