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Assessing Users' Mental Status from their Journaling Behavior through Chatbots

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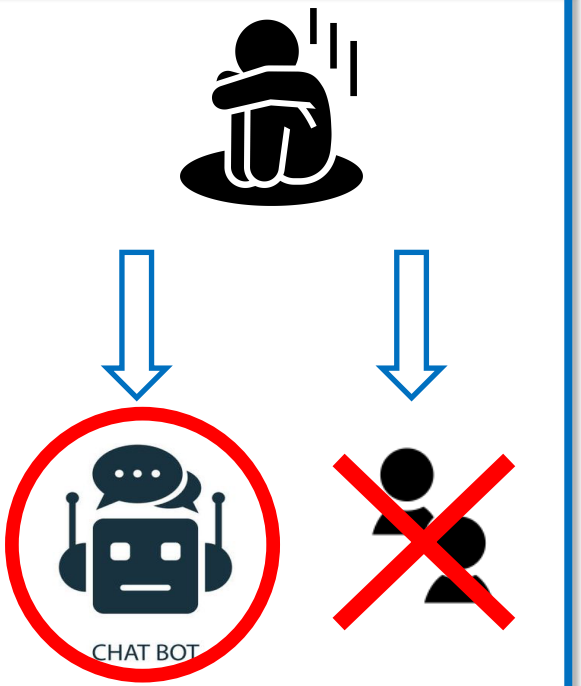
【Outline】

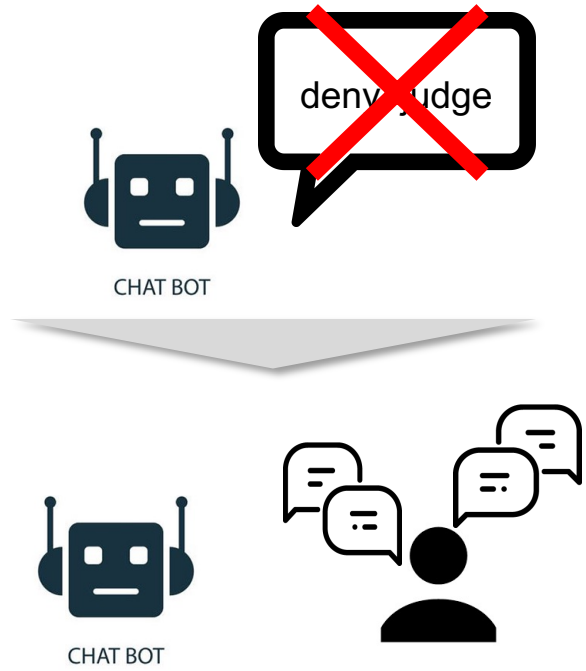
Introduction

【Introduction】 Background

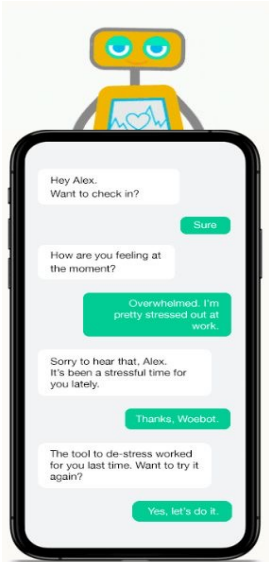
In general [1]



Benefits of using chatbots [2]



Applications of chatbots

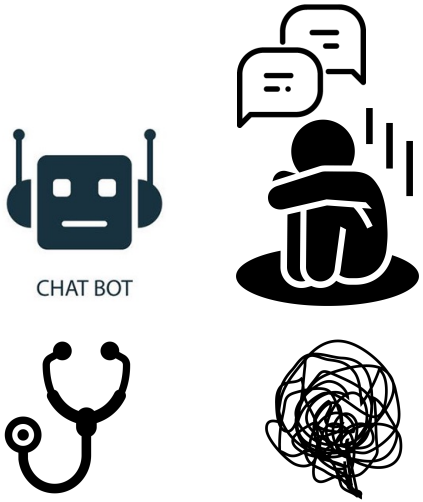


Woebot [3]
(Therapy chatbot)

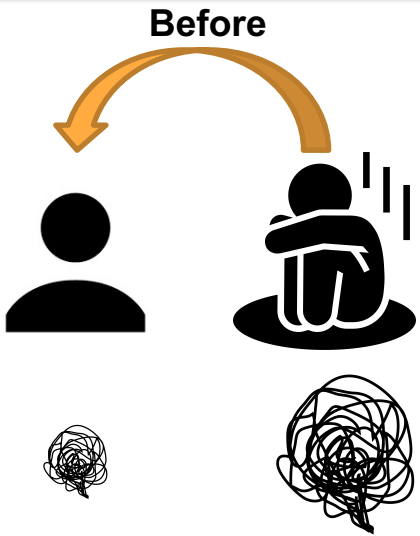
[1] Gale M Lucas, Jonathan Gratch, Aisha King, and Louis-Philippe Morency. 2014. It's only a computer: Virtual humans increase willingness to disclose. Computers in Human Behavior 37, 8 (2014), 94–100.
[2] Tim Althoff, Kevin Clark, and Jure Leskovec. 2016. Large-scale analysis of counseling conversations: An application of natural language processing to mental health. Transactions of the Association for Computational Linguistics, 4 (2016), 463–476.
[3] Kathleen Kara Fitzpatrick, Alison Darcy, and Molly Vierhile. 2017. Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): a randomized controlled trial. JMIR mental health 4, 2 (2017), e19.

【Introduction】 The Purpose of this Research

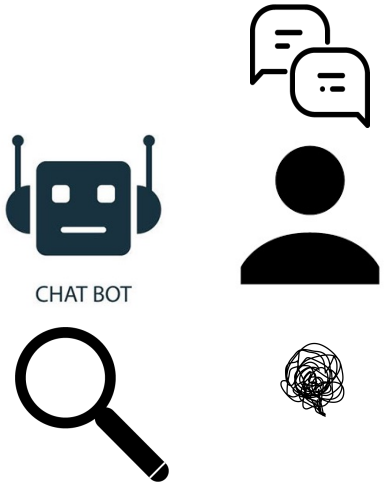
Previous research



Early detection



The aim of our research



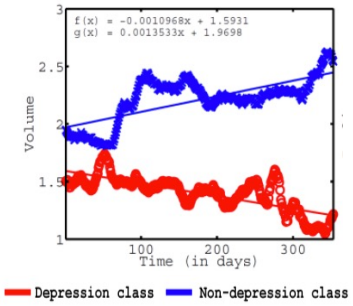
The aim of our research

to develop a tool that **estimates a user's mental status by analyzing the contents that the person daily communicates with a chatbot**

【Introduction】 Related Work + Research Question (1)

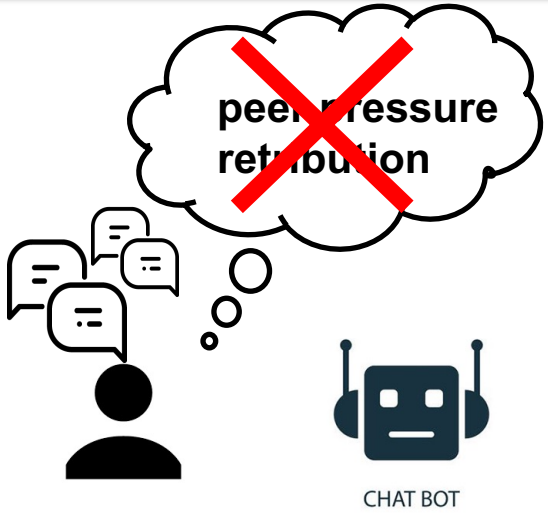
Word Counts [1]

- People's text input to social media posts **considerably decreases** when they get depressed [1].



Worry about judgement [2]

In chatbot conversations



Research Question (1)

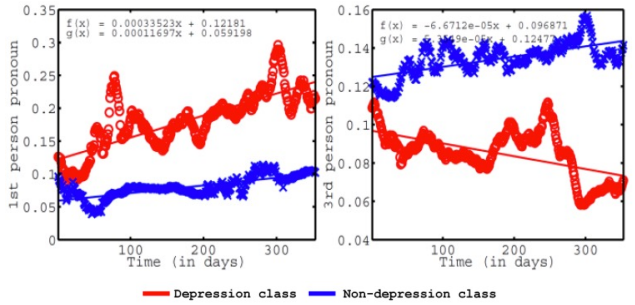
How does the amount of words change over time in chatbot conversations when people are experiencing stress or mental health issues?

[1] De Choudhury, M., Gamon, M., Counts, S., & Horvitz, E. (2013). Predicting Depression via Social Media. In Proc. ICWSM-13.
[2] Xiao Ma, Jeffrey T Hancock, and Mor Naaman. 2016. Anonymity, intimacy and self-disclosure in social media. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16), 5 (2016), 3857–3869.

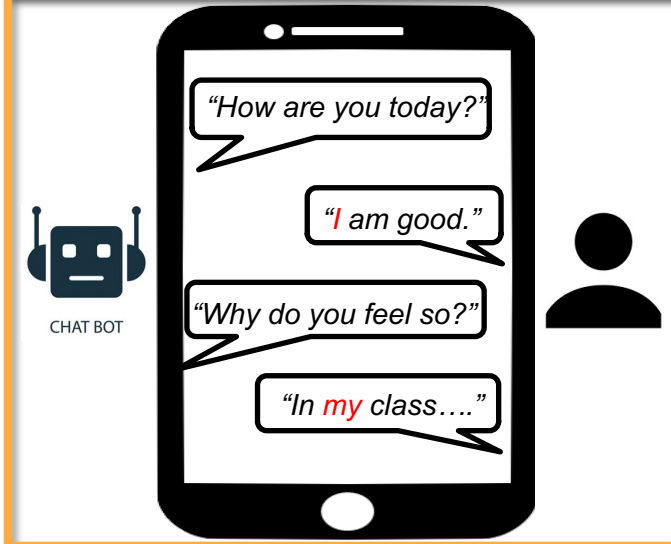
【Introduction】 Related Work + Research Question (2)

Personal Pronouns [1]

- When people are depressed, they **use more first-person pronouns** in their social media posts and **fewer third-person pronouns.**



In chatbot conversations



Research Question (2)

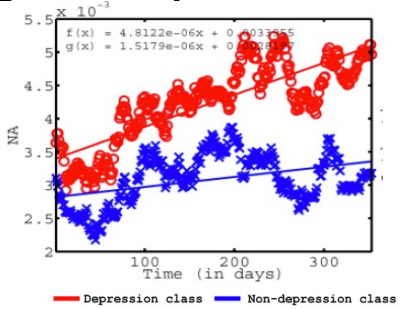
How does the use of first-person pronouns and third-person pronouns change over time in conversations with a chatbot when people are experiencing mental health issues?

[1] De Choudhury, M., Gamon, M., Counts, S., & Horvitz, E. (2013). Predicting Depression via Social Media. In Proc. ICWSM-13.

【Introduction】 Related Work + Hypothesis (1)

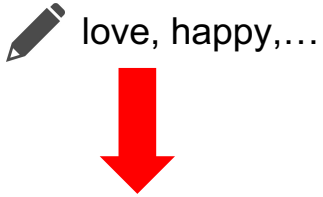
Negative Emotion Words [1]

・The use of negative emotion words in social media posts increased as the degree of depression increased.



Positive Emotion Words [2]

・Depressed people used fewer positive emotion words in their writing than the non-depressed.



Hypothesis (1)

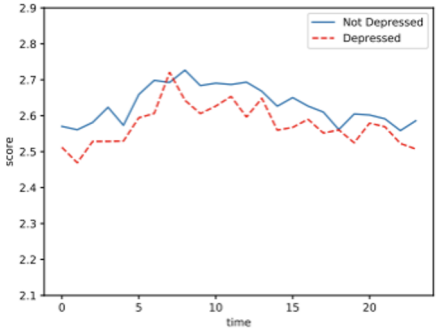
As people experience more mental health problems, their use of negative emotion words increases and their use of positive emotion words decreases over time in chatbot conversations.

[1] De Choudhury, M., Gamon, M., Counts, S., & Horvitz, E. (2013). Predicting Depression via Social Media. In Proc. ICWSM-13.
[2] Philip Resnik, Anderson Garron, and Rebecca Resnik. 2013. Using topic modeling to improve prediction of neuroticism and depression. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing (EMNLP '13), 10 (2013), 1348–1353.

【Introduction】 Related Work + Hypothesis (2)

Concrete Words [1]

・The more depressed users are, the fewer concrete words they use in their tweets.



The concreteness of word [2]

A list (40,000 words included), each assigned 1 to 5 points depending on the concreteness

Abstract (language based) 1 2 3 4 5 Concrete (experience based)

[Ex] sports (3.79) < tennis (4.43)

・Concrete：banana,octopus,egg, ...
・Abstract：belief,realism,concept, ...

Hypothesis (2)

As people begin to experience mental health issues, their use of concrete words will gradually decrease in chatbot conversations.

[1] Yifan Gao, Yuchong Zhong, Daniel Preotiuc-Pietro, and Junyi Jessy Li. 2019. Predicting and analyzing language specificity in social media posts. In AAAI 2019.
[2] M. Brysbaert, A. B. Warriner, and V. Kuperman. Concreteness ratings for 40 thousand generally known English word lemmas. Behavior Research Methods, 46(3):904–911, 2014.

【Introduction】 The Subject of this Research

Summary so far

As people experience more mental health problems, in the conversation with chatbots over time,

Research Questions

RQ1: **The amount of words change.**

RQ2: **The use of first-person pronouns and third-person pronouns change.**

Hypotheses

H1: **The use of negative emotion words increase and the use of positive words decrease.**

H2: **The use of concrete words decrease.**

The subject of this research

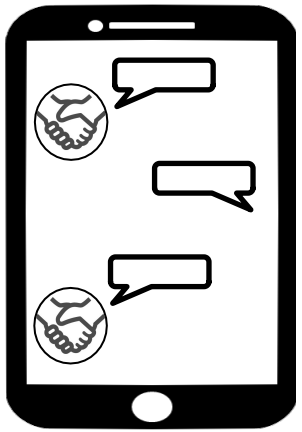
By testing our two hypotheses, we uncover **whether we can detect individuals whose mental status gradually deteriorated by analyzing chatbot conversations.**

Method

ManyChat

Dialogflow

CHAT BOT

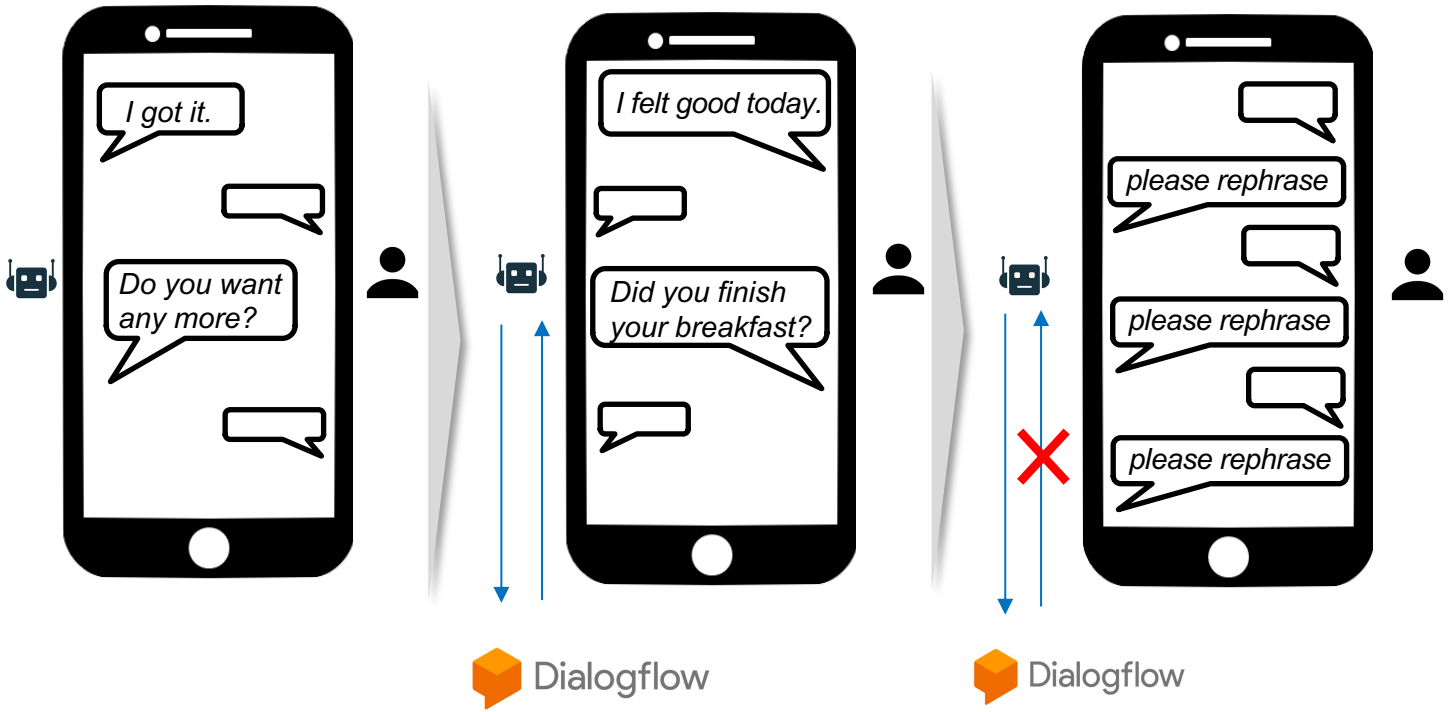


Conversation journaling regulation with the chatbot

Ask fixed and answer fixed forms

An unexpected question or response

Urged participants to rephrase



【Method】 Experimental Method

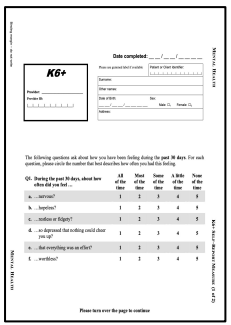
- 30 participants
  - ○ Male = 13
  - ○ Female= 17
  - ○ Age = 20～27 (M=23)

3 weeks

K6 Test → K6 Test → Analysis

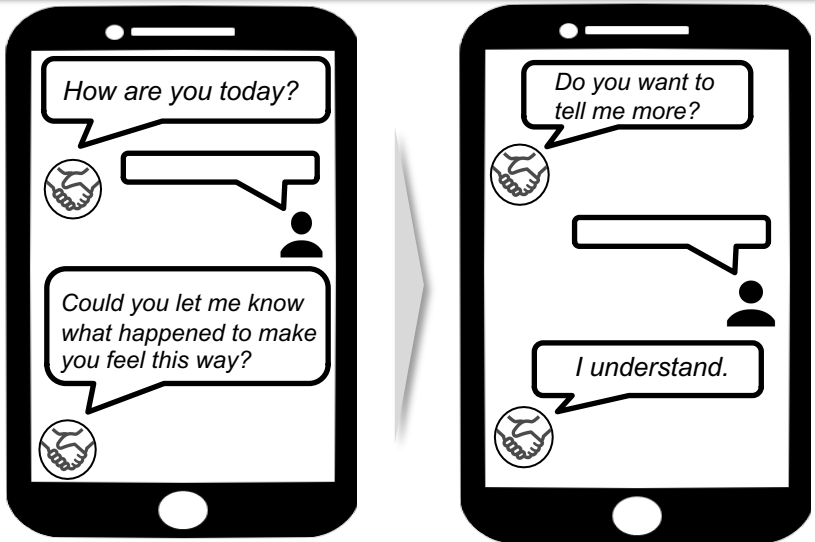
Before the experiment

Check if K6 score (the mental status) is below the standard value [1].



K6 score Low ⟷ K6 score High

Conversation journaling flow with the chatbot



After the experiment

K6 score: decreased	K6 score: unchanged	K6 score: increased
n =14	n = 7	n = 9
Improved group	Unchanged group	Deteriorated group

[1] Judith J Prochaska, Hai-Yen Sung, Wendy Max, Yanling Shi, and Michael Ong. 2012. Validity study of the K6 scale as a measure of moderate mental distress based on mental health treatment need and utilization. International journal of methods in psychiatric research 21, 2 (2012), 88–97.

【Method】 How to Analyze Conversation Logs

LIWC (Linguistic Inquiry and Word Count) [1]

- **Calculated for the following items (<u>All values are per post</u>)**

  - (1) Word counts [WC]
  - (2) The rate of Positive emotion words [PE]
  - (3) The rate of Negative emotion words [NE]
  - (4) The rate of first-person pronouns [FP]
  - (5) The rate of third-person pronouns [TP]

[Ex] I love that nice flower.

(1) WC = 5 words
(2) PE = 40%
(3) NE = 0%
(4) FP = 20%
(5) TP = 0%

The Concreteness per word [2]

- **Used a list (40,000 words included), each assigned 1 to 5 points depending on the concreteness**

Abstract (language based) 1 2 3 4 5 Concrete (experience based)

[Ex] sports (3.79) < tennis (4.43)

- **(6) Concreteness per post :**
  The sum of scores obtained by comparing words in a post with a list.

- **(7) Concreteness per word :**
  [(6) Concreteness per post] ÷ [(1)Word Counts]

Analyzed the differences in the user's conversational contents with the chatbot.

- **A mixed-model ANOVA**
- **A Tukey HSD (for post-hoc analysis with two independent variables)**
  - ○ experimental day (21 experiment days) and group (3 groups).

[1]LIWC (https://liwc.wpengine.com/)
[2]M. Brysbaert, A. B. Warriner, and V. Kuperman. Concreteness ratings for 40 thousand generally known English word lemmas. Behavior Research Methods, 46(3):904–911, 2014.

Experimental Results

【Experimental Results】 RQ1 & RQ2

Word Counts

RQ1: How does the amount of words change over time in chatbot conversations when people are experiencing stress or mental health issues?

Source	F	Prob > F	η^2	Mean
the experimental day	6.34	0.0001	0.18	70.48→61.93
group	0.54	0.58	0.19	–
the experimental day * group	0.30	1.00	0.22	–

The number of words decreased, regardless of the change in mental states before and after the experiment.

Personal pronouns

RQ2: How does the use of first-person pronouns (FP) and third-person pronouns (TP) change over time in conversations with a chatbot when people are experiencing mental health issues?

Source	F	Prob > F	η^2	Mean
the experimental day (FP)	3.20	0.0001	0.10	12.66→14.40
group (FP)	1.01	0.36	0.04	–
the experimental day * group	0.83	0.74	0.57	–

Source	F	Prob > F	η^2	Mean
the experimental day (TP)	9.10	0.0001	0.27	7.34→8.57
group (TP)	2.40	0.91	0.10	–
the experimental day * group	0.72	0.89	0.50	–

The use of first- and third-person pronouns increased, regardless of the change in mental states before and after the experiment.

【Experimental Results】 RQ2 +

First-person pronouns (FP) / Third-person pronouns (TP)

First-person pronouns | **Third-person pronouns**

RQ2 + : How much the participants talked about themselves instead of others.

FP / TP

$\frac{FP}{TP}$

- $\frac{FP}{TP} > 1$
- $\frac{FP}{TP} = 1$
- $\frac{FP}{TP} < 1$

Source	F	Prob > F	η^2	Mean (%)
the experimental day (FP / TP)	4.28	0.0001	0.15	2.66→2.50
group (FP / TP)	0.44	0.64	0.02	–
the experimental day * group (FP / TP)	0.90	0.64	0.72	–

$\frac{FP}{TP}$ → $\frac{FP}{TP}$

The increase in the use of third-person pronouns was much larger than that of first-person pronouns.

【Experimental Results】 H1 & H2

Emotional Words

H1: As people experience more mental health problems, their use of negative emotion words (NE) increases and their use of positive emotion words (PE) decreases over time in chatbot conversations.

Source	F	Prob > F	η^2	Mean (%)
the experimental day (PE)	3.46	0.0001	0.2	6.36→6.16
group (PE)	8.21	0.0003	0.02	DG:5.26 (SD=4.25) < UG: 5.92 (SD=3.93) < IG:7.50 (SD=3.88)
the experimental day * group	0.77	0.84	0.53	–

Source	F	Prob > F	η^2	Mean(%)
the experimental day (NE)	8.07	0.0001	0.10	2.07→2.24
group (NE)	8.21	0.0003	0.003	DG:2.80 (SD=2.63) > UG: 2.59 (SD=3.00) > IG:1.79 (SD=2.16)
the experimental day * group	1.23	0.12	0.86	–

People whose mental states have deteriorated gradually used **fewer positive emotion** and **began to use more negative emotion words** in chatbot conversations.

Concrete Words

H2: As people begin to experience mental health issues, their use of concrete words will gradually decrease in chatbot conversations.

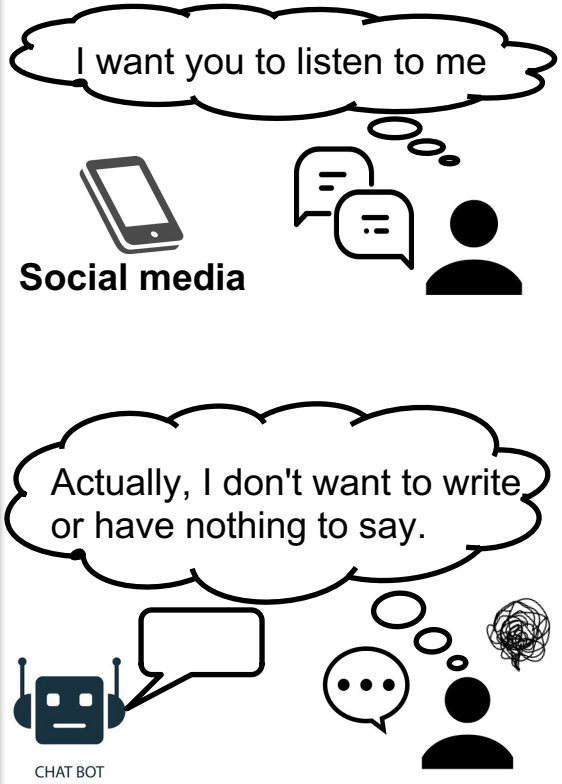
Source	F	Prob > F	η^2	Mean(min = 1 to Max =5)
the experimental day	3.67	0.0001	0.11	2.62→2.57
group	4.02	0.002	0.01	UG: 2.63 (SD=0.18) > DG:2.60 (SD=0.17) > IG:2.58 (SD=0.16)
the experimental day * group	0.59	0.97	0.41	–

People whose mental states have deteriorated during the study gradually **used fewer concrete words**.

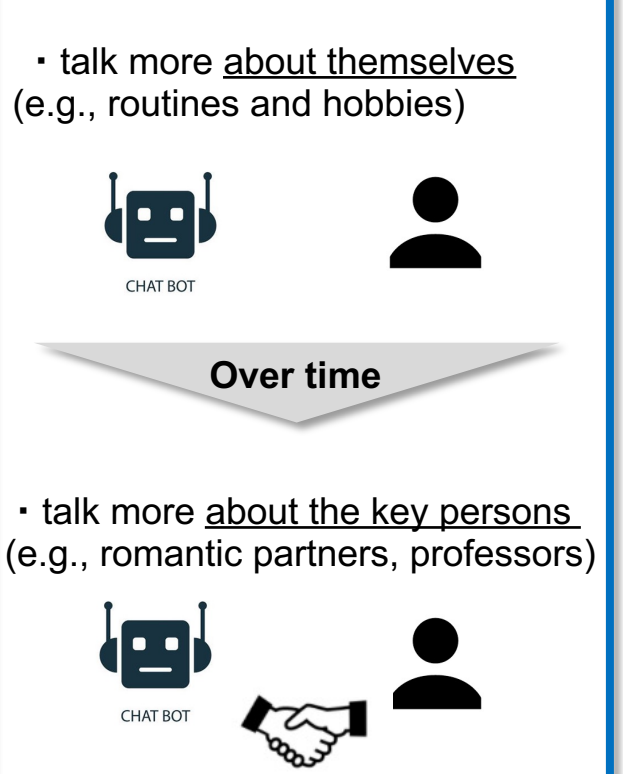
Conclusion & Future Work

【Conclusion & Future Work】 Discussion

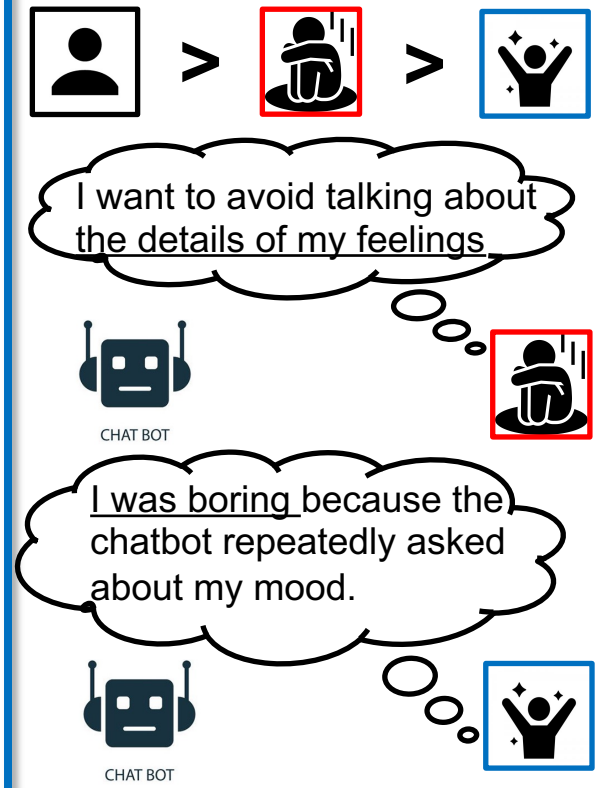
Why did the number of text entries decrease?



Why did the third-person pronouns increase?



Why did the use of concrete words decrease?



【Conclusion & Future Work】 Conclusion

Conclusion

・We can detect a person whose mental status has deteriorated from self-disclosure data through chatbots.

・People whose mental states have deteriorated during the study gradually **used fewer positive emotion words and concrete words, and began to use more negative emotion words** when describing their daily experiences and feelings to the chatbot.

Future Work

・By combining the results of this study with counseling chatbots, people whose mental status has deteriorated can be led to the treatment phase.

・A study that compares different types of chatbots or a Wizard of Oz study (that replaces the chatbot with a real human).

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