Birds of a Feather: Clustering Mental Models to Explore How People Think Alike

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The Bottom Line Up Front

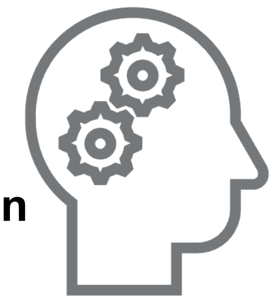
- Automate the process of analyzing the collective mental models of a group from text.
- Increase efficiency and scale-up analysis for larger samples and groups.
- Utilized generative artificial intelligence (AI), network science, and clustering.

Mental models

internal, cognitive representation of how one understands and interprets the world around them (Forrester 1971, Senge 2000).

- Help simplify the world; help "make sense" of it
- Implicit: includes beliefs, assumptions, and preferences
- Influence our daily decisions
- People have different mental models:

  A major barrier for shared understanding, organizational learning, and collective decision making.



There are also implications for group model building and thus system dynamics modeling.

Grand challenge: How to analyze a group of mental models

- Multiple ways to collect people's mental models
  - Surveys, interviews, games, vignettes, **text data**
- Analyzing mental models is labor intensive (Kim, 2009; Kim & Andersen, 2012)
- Strengths and weaknesses of different analysis techniques

Gathering and analyzing mental models can be difficult to do for several reasons.

Method

1. Employ a network science approach to analyze a large set of mental models derived from text data
   - Transition from text to maps, and from maps to causal matrices
   - Compare the matrices
   - Apply community clustering to matrices
     - **To showcase**: we collect data from a sample of participants
2. Validate our approach by comparing our identified clusters with clusters derived from a different survey

Data collection

- We gather data from Eng. Undergraduate students at Virginia Tech
- Each individual received this prompt:

  "What effects do you think ChatGPT will have on the world? In your own words, please write a few sentences to a paragraph describing these factors and impacts."

- Response rate: n=64
  - Also collected demographic and psychographic data
  - And asked them about their response, e.g. what was important to them as they responded

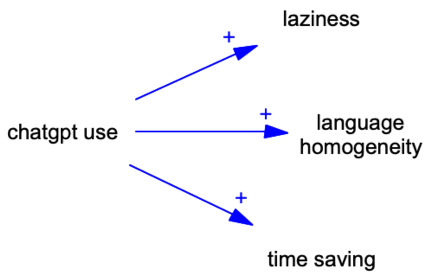
Which demographic and other validation to collect was informed by previous studies. See Davis et al. (2023) and Liu et al. (2024).

From text to map: SD Bot utilized

Hosseinichimeh, et al., 2024

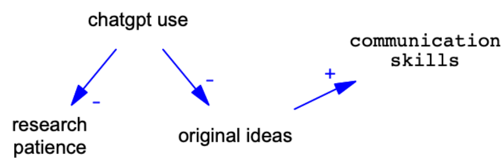
Example 1:

"I think it can bring about laziness. LinkedIn nowadays sounds like all the same person. I do think it help save time in multiple ways."



Example 2:

"I think that people will have a hard time writing and coming up with their original ideas. As a result, we as a society will regress in our ability to communicate effectively without the aid of technology. People will also become more impatient when it comes to researching answers on their own."



The System Dynamics Bot (SD Bot) takes text as input and identifies variables and causal relationships. See Hosseinichimeh, N., Majumdar, A., Williams, R. and Ghaffarzadegan, N. (2024), From text to map: a system dynamics bot for constructing causal loop diagrams. Syst. Dyn. Rev., 40: e1782. https://doi.org/10.1002/sdr.1782.

Causal matrix construction

We turn each text/map to one matrix.

Text
"I think it can bring about laziness… I do think it helps decrease time spent in multiple ways."

ChatGPT use → *(+) laziness*
ChatGPT use → *(-) time spent*

1 for increase, -1 for decrease, 0 for no effect/mention

Variable names	ChatGPT use (it)	Laziness	Time spent	….	…
ChatGPT use (it)	0	1	-1	0	0
Laziness	0	0	0	0	0
Time spent	0	0	0	0	0
…	0	0	0	0	0
…	0	0	0	0	0

Variables used by others but absent in this response

From matrices to shared maps

So far: one matrix per individual with the same variable labels in order

Consider these two matrices (coming from two individuals, A_1 and A_2):

$$A_1 = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \text{ and } A_2 = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}$$

Collective map of the two: $A_1 + A_2 = \begin{bmatrix} 0 & -1 \\ 2 & 0 \end{bmatrix}$

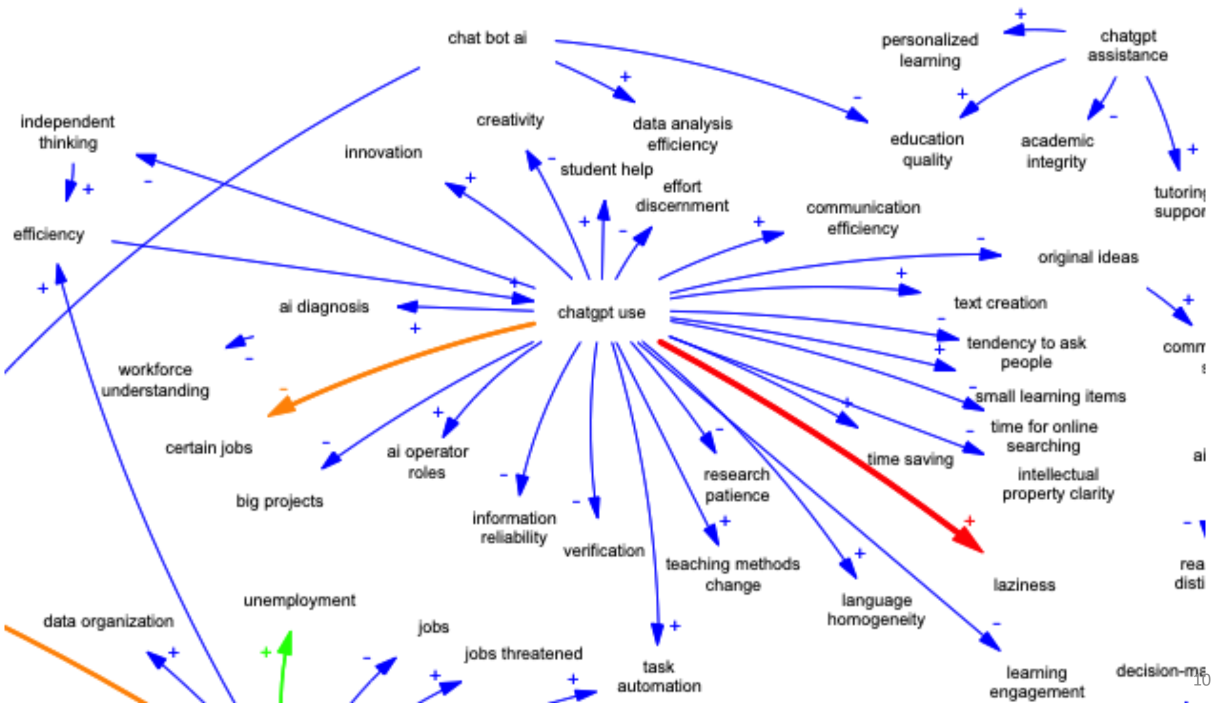
-- shows one of the causal links is more commonly mentioned

Scaling up: A collective map can be plotted by calculating

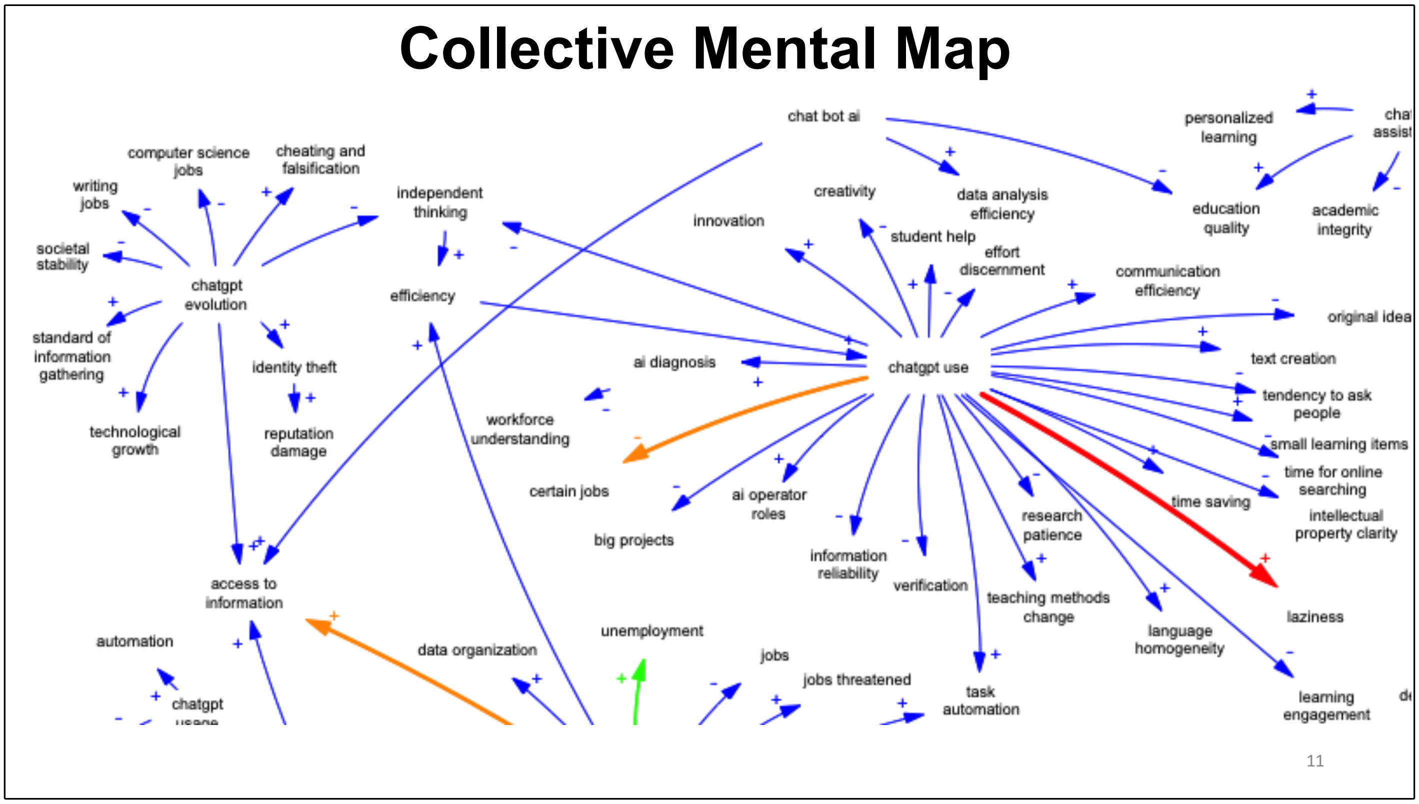
$$\sum_{i=1}^{n} A_i$$

Let's check our dataset of n=64 ➔

Collective Mental Map

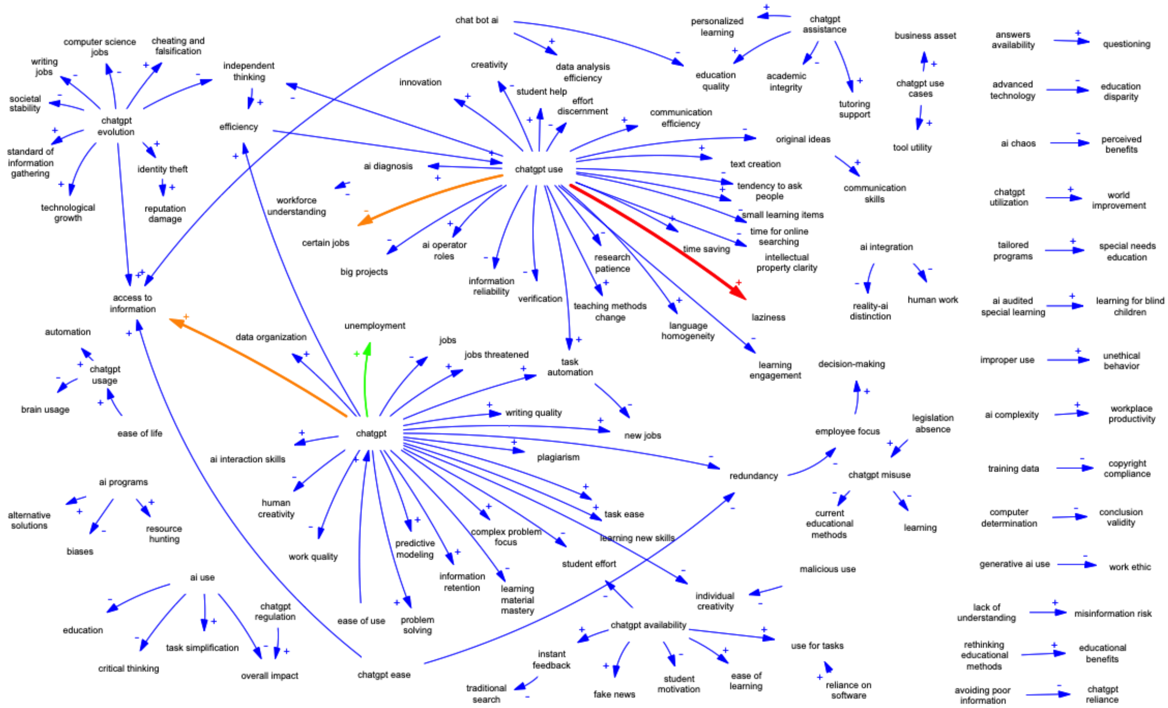


A section of the collective mental map from these participants. Color and link thickness indicate number of mentions. For example, several participants mentioned that an increase in "chatgpt use" would result in an increase in "laziness."



Zooming out on more of the collective mental map.

Collective Mental Map



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The entire collective mental map. Some variables were only mentioned once (on the right).

Using matrices to cluster individuals

Consider again these two matrices (two individuals, A_1 and A_2):

$$A_1 = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \text{ and } A_2 = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}$$

Calculate the distance between the two: $A_1 - A_2 = \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix}$

- This says there is one link that they disagree on
- But they agree on the other link
- We define the distance between these individuals, A_1 and A_2 as |-1|=1

Scaling up: The distance between any pair

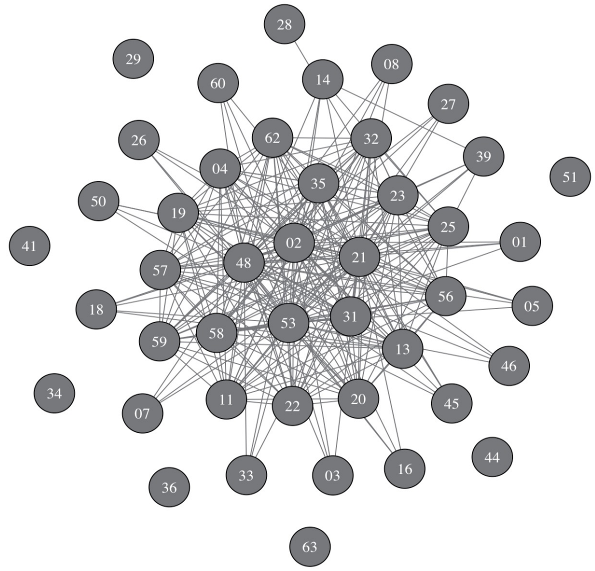
$$A_{nxn} = [a_{ij}] \text{ and } B_{nxn} = [b_{ij}], \text{ is } \sum_{i,j}^{n} \left|\boldsymbol{a_{ij}} - \boldsymbol{b_{ij}}\right|$$

- Let's check our dataset of n=64 ➔

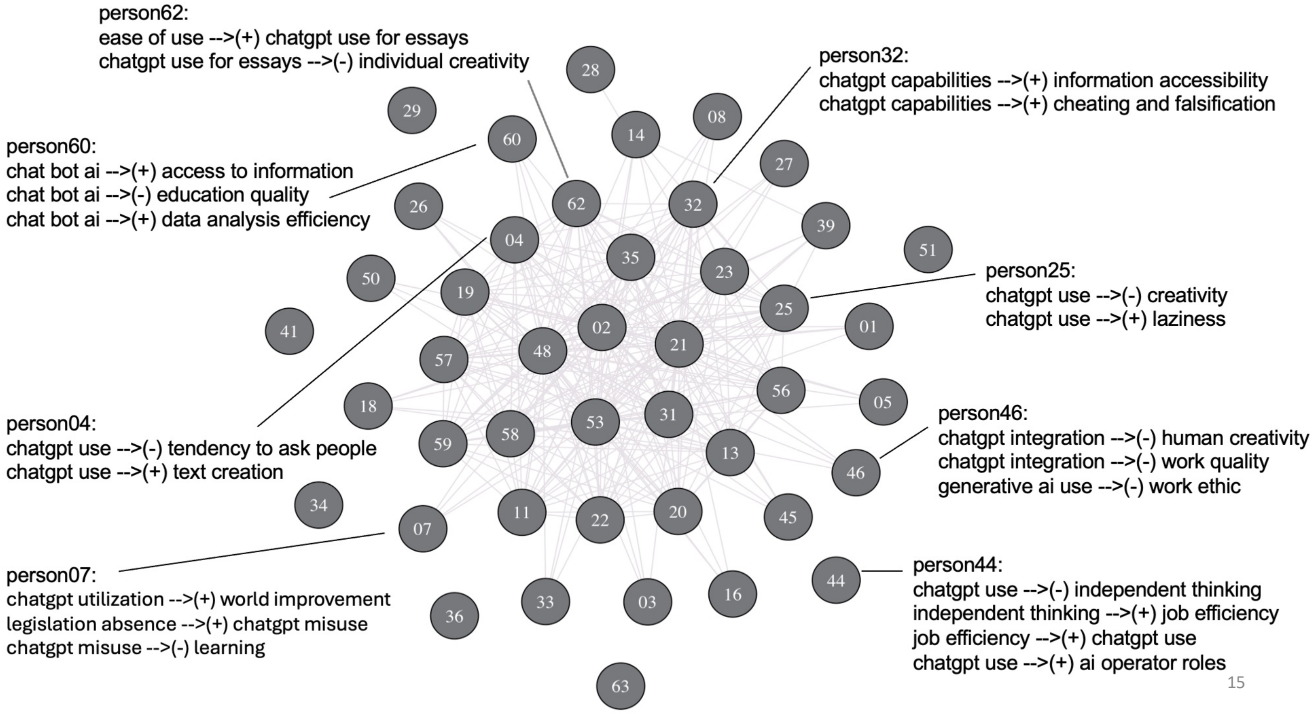
Network representation

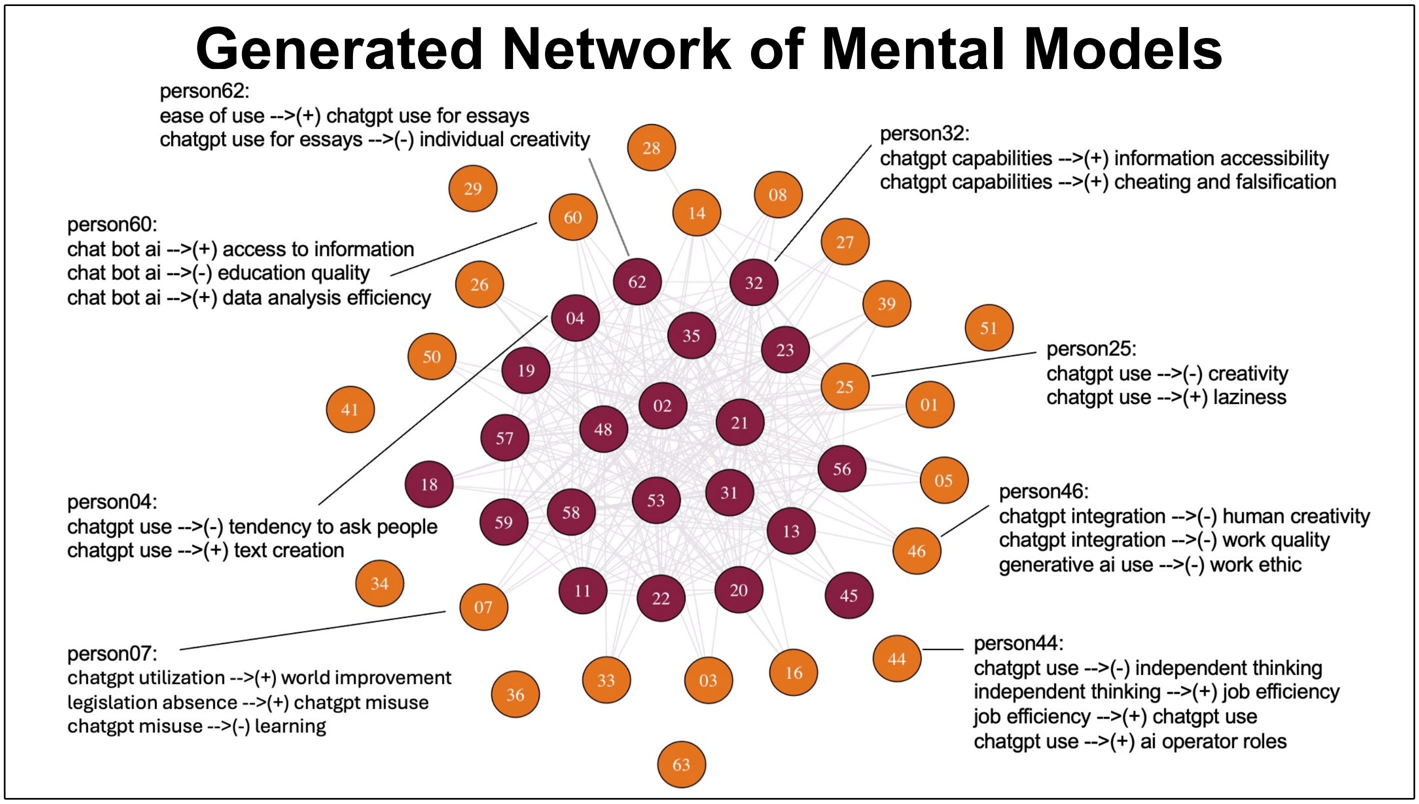
- The nodes are people
- The edges are distances

- People who think similarly are closer in the network



Generated Network of Mental Models





The colors represent the results of community detection / clustering.

Two communities were detected

- **Skeptical Realists** (21 members; maroon)

  Express **concerns** about the potential negative impacts of ChatGPT, particularly for **students**, while acknowledging the practical **benefits**.

- **Revolutionary Change** (23 members; orange)

  See ChatGPT as a **transformative** tool that will bring significant positive changes to the way work is conducted. Many have **unique** individual thoughts **different** from the Skeptical Realists.

We uploaded the original text along with a community/cluster label and asked ChatGPT for help in categorizing these two clusters.
Interestingly, in this group of participants, the second (orange) cluster is partly defined by not being in the first (maroon) cluster.

So far

- We used Generative AI to analyze mental models of a group members, depict collective mental model, and cluster them
- Validation question: Are these clusters revealing anything?
  - We use a logistic regression model to predict community membership using other data

If we can predict the clusters separately using the other data we collected (demographics, own response categorization, etc), then that would provide evidence supporting the validity of this new approach.

The model can predict community

Response Categorization	Psychographics	Demographics

Variable	Coefficient Estimate	p-value
ImportanceEthics*	-1.86	0.033*
ImportanceApplications*	-2.12	0.028*
CategoryEthical*	2.73	0.048*
ThreatAI*	-1.42	0.014*
CurrentChatGPT*	-3.85	0.028*
WorkExperience	-0.60	0.094
USCitizen	2.05	0.154
FrequencyChatGPT*	1.73	0.028*
Woman	1.55	0.087

*statistically significant at the 95% confidence level (alpha = 0.05)

Interesting that the clusters were defined in part by concerns for students, while in the model variables for the importance of ethics while one was answering, categorizing one's own response as being about ethics, seeing AI as a threat, and applications (education is an application) were significant predictors. The model is evidence for the validity of the new approach.

Key takeaways from this work:

- Offers a different approach for analyzing a group of textual mental models, employing automation for efficiency and scale.

- Contributes to the literature of systems thinking and social learning.

The SD Bot allows analyzing text at large scales and will only continue to improve.

Thank you!
Are there any questions?

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