

Understanding, Formalizing, and Reconstructing Mental Models with an Online Tool for Serious Discussions

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Certificate of Original Authorship

I, *Madiha Anjum*, declare that this thesis, submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the *School of Computer Science, Faculty of Engineering & IT* at the University of Technology Sydney, Australia.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Abstract

We live in a time when humanity faces many existential threats - climate change, resource depletion, biodiversity loss, and refugee crises. Wicked problems need to be properly approached and cannot be solved without human participation. These problems require stakeholder participation, which is hard to organize and support. Participatory modeling is one method that facilitates stakeholders' engagement in the decision-making process and enables collaboration to achieve a mutually acceptable solution. Mental models are essential tools in participatory modeling as mental models are informal representations of how the world works. The way we perceive, behave, and decide is also dependent on and influenced by our mental models. Direct observation, learning, and experience can help in maintaining and updating our mental models. At the same time, mental models are constantly relied upon to reason, explain, design, communicate, act, predict, and explore. Overall mental models play an essential role across all domains of human agency so, a tool that can help to formalize computer simulations from the mental models expressed by a group within a given problem situation will be of much benefit for experts and practitioners from various fields like behavioural science, psychology, economics, education, and sustainability as they can gain many insights.

We have developed a real-time, moderated tool, named Discussoo, for understanding and formalizing mental models of participants of online discussions. Users are presented with a topic, question, or problem to debate, on which they can express their opinions/thoughts in the form of comments. Users can also respond or expand on other users' opinions and/or initiate a new line of discussion. The discussion chain is then mined in real-time, using an ensemble of algorithms (including but not limited to concept mining, topic modeling, and sentiment analysis) to extract opinions, keywords, and concepts. This information is transcribed into formal models using Concept maps, Causal Loop Diagrams, and Networks Diagrams as the discussion evolves. To provide feedback, the system presents users with dynamic visualizations of the collective mental model, which they can use as contextual information to refine and update their individual mental models. Targeted moderator comments can also introduce feedback to steer or "nudge" the discussion towards a desirable collective mental model, outcome, consensus, or agreement.

Discussoo can be used in a variety of settings and problem situations, where the steering of collective mental models could improve the functioning, resilience, or sustainability of a given (social, environmental, or technical) system or used by policy makers or any other organization who would benefit from a more direct, transparent and meaningful engagement of their stakeholders.

To my parents

List of Publications Related to this thesis:

Journals:

Anjum, M., Voinov, A., Taghikhah, F. and Pileggi, S., 2021. Discussoo: Towards an intelligent tool for multi-scale participatory modeling. *Environmental Modelling & Software*.

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Bakhanova, E., **Anjum, M.**, Voinov, A., Raffe, W. & Garcia Marin, J. (2021). Gamification of Discussoo: an online AI-based forum for serious discussions, 24th International Congress on Modelling and Simulation, Sydney, Australia

Anjum, M., Voinov, A Pileggi, SF 2019(2020). Eliciting, Formalising, And Debiasing Mental Models Through an Online Tool For Serious Discussions, *iEMSs2020, Brussels, Belgium*

Anjum, M., Voinov, A, Castilla Rho, J & Pileggi, SF 2019, 'Understanding mental models through a moderated framework for serious discussion', 23rd International Congress on Modelling and Simulation, Canberra.

Table of Contents

- Abstract..... 3
- List of Publications Related to this thesis: 6
- Chapter 1: Introduction 13**
- 1. Overview.....13
- 2. Introduction.....14
- 3. Research Goal, Objectives, and Research Questions16
- 4. Research Limitations.....17
- 5. Research Methodology and Design18
- 6. Outline of the Thesis.....21
- 7. Note on COVID 19 Impact on this research 22
- Chapter 2: An online, AI-powered, tool for moderating serious discussions and fostering stakeholder engagement.....23**
- 1. Overview..... 23
- 2. Abstract..... 24
- 3. Introduction..... 25
- 4. Review of existing text mining and computational linguistics techniques..... 29
- 5. An online AI-Based Tool for serious discussion: Discusoo37
- 6. Discusoo Engine (real-time analysis of discussions) 45
- 7. Gamification of Discusoo: An agent that facilitates the discussion: 53
- 8. Adding the chatbot functionality to encourage post engagement 58
- 9. Case Study..... 63
- 10. Discussion 65
- 11. Conclusions..... 68
- Chapter 3: Discusoo: Towards an intelligent tool for multi-scale participatory modeling..... 69**
- Overview 69

| | |
|--|------------|
| Chapter 4: Formalising Mental Models from Online Discussions: An Application of the Discusoo Platform | 71 |
| 1. Overview..... | 71 |
| 2. Abstract..... | 72 |
| 3. Introduction..... | 73 |
| 4. Background..... | 77 |
| 4.1. Mental Models and applications | 77 |
| 4.2. From Individual to Group Mental Models..... | 80 |
| 4.3. The Mental Model Creation Process | 81 |
| 5. Exploring gaps in mental model elicitation, analysis and representation..... | 84 |
| 5.1. How to elicit mental models..... | 84 |
| 5.2 How to analyze mental models..... | 86 |
| 5.3 How to present mental models..... | 91 |
| 5.4. How to address gaps in mental model | 92 |
| 6. Exploring mental models with Discusoo: Australian community energy case study | 99 |
| 6.1. Opinion collection and stakeholder engagement | 99 |
| 6.2. Discussion analysis..... | 101 |
| 6.3. Discussion representation | 103 |
| 6. Discussion..... | 104 |
| 7. Conclusions..... | 108 |
| Chapter 5: Reconstructing mental models through a moderated framework for serious discussion..... | 110 |
| 1. Overview..... | 110 |
| 2. Abstract..... | 111 |
| 3. Introduction..... | 112 |
| 3. Methodology:..... | 117 |
| 4. Case Study:..... | 120 |

| | |
|--|------------|
| 5. Data Analysis | 121 |
| 6. Data cleaning and pre-processing | 122 |
| 7. Results and Discussion: | 122 |
| 8. Conclusion: | 137 |
| Chapter 6: Conclusion | 138 |
| 1. Development of an AI based online, moderated tool for serious discussion | 138 |
| 2. Facilitating PM workshops using Discusoo | 139 |
| 3. Mapping Mental Models from an Online Discussions platform..... | 140 |
| 4. Reconstructing mental models through a moderated framework for serious discussion | 141 |
| 5. Research Contributions | 142 |
| 6. Why use Discusoo | 143 |
| 7. Future Research..... | 143 |
| Appendix..... | 145 |
| Bibliography..... | 152 |

List of Figures

| | |
|--|----|
| Figure 1.1. Text Analysis phases | 20 |
| Figure 2.1. Discussoo Framework | 29 |
| Figure 2.2. Categories of NLP algorithm (source: self-elaboration based on literature)..... | 36 |
| Figure 2.3. Challenges in using NLP (source: self-elaboration based on literature) . | 36 |
| Figure 2.4. Users can get involved in the discussions by pressing the join button ... | 38 |
| Figure 2.5. Admin can approve/edit/delete discussions in Discussoo..... | 39 |
| Figure 2.6. Admin can sort discussions based on title, group, comment count, and date created in Discussoo. Admin can also rearrange/pin discussion by using drag and drop features..... | 40 |
| Figure 2.7. Admins can enable or disable the chatbot and the game in all the discussions..... | 41 |
| Figure 2.8. Creating/Editing/Deleting Groups in Discussoo | 41 |
| Figure 2.9. Admins can enable and disable the following features in any discussion. (Reply, Score, Sharing)..... | 42 |
| Figure 2.10. Admin can create new users on the platform | 43 |
| Figure 2.11. Admin can add trending topics to the home page..... | 43 |
| Figure 2.12. Rearranging the Comments | 44 |
| Figure 2.13. Admin can act against reported comments | 45 |
| Figure 2.14. Conceptual framework of Discussoo..... | 45 |
| Figure 2.15. Five phases that are involved in the creation of conceptual models from the discussion | 46 |
| Figure 2.16a. Unfiltered Conceptual Diagram | 52 |
| Figure 2.17. Influencer badges | 56 |
| Figure 2.18. Bubble Shooter Game | 57 |
| Figure 2.19. Loopy embedded in Discussoo..... | 58 |
| Figure 2.20. Flowchart of chatbot in Discussoo | 61 |
| Figure 2.21. Chatbot is suggesting a similar comment to the user and inviting feedback on that comment | 62 |
| Figure 2.22. Chatbot is responding to user's comment by adding a new comment... | 62 |
| Figure 2.23. Examples of comments added by the chatbot in the discussion..... | 63 |
| Figure 2.24. Response of students about the user experience of Discussoo | 64 |
| Figure 2.25. Response of students about the user experience of Discussoo | 64 |
| Figure 2.26. Word cloud of response from students when they were asked about "What did they liked the most about Discussoo" | 65 |

| | |
|---|-----|
| Figure 2.27. How Discussoo can address the challenges in serious discussion forums..... | 66 |
| Figure 2.28. Applications of Discussoo..... | 67 |
| Figure 4.1. Process of formation, refining, and updating of a mental model..... | 83 |
| Figure 4.2. Techniques used in Discussoo for each phase of Mental model formation..... | 97 |
| Figure 4.3. Community energy concept phrase and word cloud generated in Discussoo..... | 100 |
| Figure 4.4. Sentiments extracted from the community renewable energy discussion..... | 103 |
| Figure 4.5. The Clusters and the Arc Diagram..... | 105 |
| Figure 5.1. Mental models and Real-world consequences..... | 113 |
| Figure 5.2. The Ladder of Inference..... | 119 |
| Figure 5.3. Ladder of Inference and Case Study questions..... | 120 |
| Figure 5.4. Results of Questions 1 (Pre and Post Survey)..... | 123 |
| Figure 5.5. Comparison of Questions 2 (Pre and Post-Survey)..... | 125 |
| Figure 5.6. Comparison of Questions 3 (Pre and Post Survey)..... | 126 |
| Figure 5.7. Comparison of Questions 4 (Pre and Post Survey)..... | 126 |
| Figure 5.8. Comparison of Questions 5 (Pre and Post Survey)..... | 128 |
| Figure 5.9. Comparison of Questions 6 (Pre and Post Survey)..... | 129 |
| Figure 5.10. Comparison of Questions 7 (Pre- and Post-Survey)..... | 130 |
| Figure 5.11. Comparison of Questions 8 (Pre- and Post-Survey)..... | 131 |
| Figure 5.12. Representing line graph of relative frequencies in Pre survey responses..... | 132 |
| Figure 5.13. Representing line graph of relative frequencies in Post survey responses..... | 133 |
| Figure 5.14. Results about “Discussoo can assist in 'observing data', 'selecting data', 'adding meanings to the data', 'making assumptions', and 'coming up to conclusions’”..... | 134 |
| Figure 5.15. Results about “Discussoo can assist in 'observing data', 'selecting data', 'adding meanings to the data', 'making assumptions', and 'coming up to conclusions’”..... | 135 |

List of Tables

| | |
|--|-----|
| Table 1.1. Main phases of the research and methodologies applied | 18 |
| Table 2.1. A review of existing text mining and computational linguistics techniques | 31 |
| Table 2.2. Test results of Concept/ Keyphrase Extraction of bigrams or trigrams instead of unigrams (i.e., concept phrase (2-3 words) instead of concept word) using techniques like Tfidf, TopicRank, and TextRank..... | 46 |
| Table 2.3. Results for extracting clusters (Grouping of related words into clusters along with assignment of a topic to each cluster) | 50 |
| Table 2.4. Results of extracting Sentiments..... | 54 |
| Table 2.5. Results of testing different Chatbots | 60 |
| Table 4.1. A list of mental model elicitation techniques, applications, and limitations..... | 88 |
| Table 4.2. A summary of mental model analysis techniques, their advantages, and limitations..... | 94 |
| Table 4.3. A comparison of mental model representation techniques | 95 |
| Table 4.4. A list of identified gaps in mental model elicitation, analysis and presentation that are addressed by Discussoo..... | 98 |
| Table 5.1. Results of Questions 1 (Pre and Post Survey: Question 1)..... | 123 |
| Table 5.2. Results of Questions 2 (Pre and Post Survey) | 124 |
| Table 5.3. Results of Questions 3 (Pre and Post Survey) | 125 |
| Table 5.4. Results of Questions 4 (Pre and Post Survey)..... | 127 |
| Table 5.5. Results of Questions 5 (Pre and Post Survey) | 127 |
| Table 5.6. Results of Questions 6 (Pre and Post Survey)..... | 128 |
| Table 5.7. Results of Questions 7 (Pre and Post Survey) | 129 |
| Table 5.8. Results of Questions 8 (Pre- and Post-Survey)..... | 130 |

Chapter 1: Introduction

1. Overview

We live in a time when humanity faces many existential threats - climate change, resource depletion, biodiversity loss, refugee crises, etc. (Voinov et al., 2018). Participatory Modeling (PM) is one of the most practical methods to facilitate stakeholders' engagement in the decision-making process and enable collaboration to achieve a mutually acceptable solution (Sterling et al., 2019). Mental models are essential tools within the field of participatory modeling (LaMere et al., 2020). They are informal representations of how the world works and can influence how we perceive reality and how we behave and make decisions based on our perceptions. Direct observation, learning, and experience can help in maintaining and updating our mental models. At the same mental models are constantly relied upon to reason, explain, design, communicate, act, predict, and explore. This thesis presents transdisciplinary research that aims to create an online, real-time, moderated forum that will help us better comprehend and formalize mental models (MM) that emerge from online discussions. Overall mental models play an essential role across all domains of human agency, so a tool that can help to formalize computer simulations from the mental models expressed by a group within a given problem situation will be of much benefit for experts and practitioners from various fields like behavioural science, psychology, economics, education, and sustainability.

2. Introduction

Web platforms for online discussions can contribute to the participatory process by providing a space for sharing perspectives between different groups of stakeholders and supporting collective decision-making. Such tools can be particularly useful in the context of PM, ‘a purposeful learning process for action that engages stakeholders’ implicit and explicit knowledge to create formalized and shared representations of reality’ (Jordan et al., 2018). Traditionally PM is organized in the form of face-to-face modeling workshops that have limitations in terms of the number of participants and their time availability. Unlike traditional methods of group discussions, web-based communication tools are commonly used for targeting a wider audience, encouraging more diversity of perspectives. However, to have a focused discussion and extract useful insights, such techniques usually require effective moderation that is expected, among others, to guarantee that the participants’ points of view are equally considered.

Online discussion forums used for citizen deliberation and community engagement require to be moderated cautiously. On the one hand, online forums can help to address challenges related to social hierarchies (Wojcik, 2008), making the discussion process more open for everyone. On the other hand, using those tools can lead to undesired and unintended results in public participation. For example, Lampe et al., (2014) and Wright (2009) argued that polarization of the debates and hostility (e.g., flaming and trolling) might undermine the quality and the purpose of the discussion process. Likewise, Kearns et al., (2002) suggested that unstructured discussions can lead to chaos – ‘free speech without regulation becomes just noise’ – where the loudest or the most active participant takes over the whole debate.

Complex social problems, also known as wicked problems, are defined by their complexity, uncertainty, set of interrelated subproblems, recursive dependencies, and multiple interpretations (Vennix, 1996). Therefore, they are difficult, or even impossible to solve. Partly, because the requirements to solve a wicked problem tends to change according to the context where it takes place. Hence the multiple possible solutions to the same wicked problem. The diversity of possible solutions to a wicked problem implies that it is unlikely that the same solution can be applied in two different contexts. Despite the complex nature of wicked problems, communities can be quite effective in finding solutions in their own context. Finding those solutions

requires that members of a community speak to each other, share their opinions, and engage in a discussion that can lead to some compromise and shared understanding.

Recent advances in the different fields of AI, such as Natural Language Processing (NLP), allow us to automatically extract information from online discussion forums and analyze this information in real-time. This is particularly useful in the context of PM, where a group of stakeholders develops a model of a system in question with the help of a facilitator. Such potential technological support creates a foundation for developing conceptual models based on the comments from the online forum.

Therefore, this research aims to develop an online moderated forum that can capture the MM that emerges from discussions and present them in some formal, visually appealing way. These models can then be displayed in the web platform where the discussion occurs, providing instant feedback to the participants about the course of the discussion and the core ideas that come to light. This should help to maintain coherent and productive discussions, even with the limited involvement of a human moderator.

Discusoo is a web platform that captures the opinions of users using an ensemble of NLP techniques to automatically synthesize the opinions expressed by the community into some visualization of the group MM that can be further presented as other conceptual, semiquantitative models. From users' comments, the system developed captures users' (1) concepts, (2) topics, and (3) sentiments which are further analysed in the form of clusters where clusters represent how different concepts are linked or related to each other. These elements are the building blocks for dynamic semi-quantitative models, such as word clouds, cognitive maps, and network maps. Discusoo allows the moderator (who would be appointed by the problem holder - researcher, government agency, or non-profit organization) to extract and analyze cognitive maps that provide relevant and actionable insights about the MM from the members of a community. As mentioned above, these results can be fed back into the discussion, with further research conducted about their role in informing participants and helping them to find improved solutions to complex and controversial societal issues.

The platform might be particularly useful for engaging researchers, stakeholders, and decision-makers in the participatory process, with no restrictions regarding the size of the group nor the timing and location of their meetings.

3. Research Goal, Objectives, and Research Questions

This research aims to develop a framework that captures representations of a group's mental model from an online web forum and translates these into conceptual models. The framework should allow the moderator (a researcher, government agency, or non-profit organization) to extract and analyze cognitive maps that provide relevant and actionable insights into questions about the structure and evolution of a group's mental model concerning a particular topic. The framework should provide both users and moderators with the information needed to understand and formalise the group's mental model and in doing so, produce new and creative solutions to complex and controversial societal issues.

The research objectives include the following:

1. Compare and analyze existing text mining and computational linguistics techniques to identify those approaches which are most suited for eliciting the building blocks of MM (concepts, topics, opinions, sentiments, links/relationships etc.) (Chapter 2 and 4):

RQ1: What are the building blocks of a MM?

RQ2: How can these building blocks be synthesized and combined to glean valuable insights into a collective MM?

RQ3: Which text mining and natural language processing techniques/approaches have been used for analyzing people's opinions on a given topic or problem?

2. Develop a dynamic automated framework to translate the opinions expressed in the discussion forum into conceptual models (Chapters 3):

RQ4: How do we translate opinions expressed in any online discussion into semiquantitative conceptual models?

RQ5: How to formalize a semi-quantitative MM's elements (nodes, links, and weights)?

RQ6: How can participatory modeling benefit from such a framework?

3. Develop a real-time and moderated online communication/discussion tool to involve/engage people in discussions (Chapter 2):

RQ7: Identify and implement key features and requirements (from a UX perspective) to develop a user-friendly and engaging tool for online discussions?

RQ8: How to define/embed the moderator's role and responsibilities in the tool?

RQ9: How to analyze and track real-time discussions in the tool/discussion platform?

4. Explore the role that feedbacks, and visualizations play in the process of restructuring/steering a collective mental model, i.e., would users restructure knowledge and update their mental models based on their interactions with the proposed framework. (Chapters 5):

RQ10: Would participants' mental models regarding a certain context (Case study) change as a result of engaging with interactive discussion forum?

RQ11: If so, how can we measure these changes?

RQ12: How can moderators nudge the behaviour of users in an online discussion?

4. Research Limitations

This thesis develops a tool for the automatic synthesis of users' mental models during online discussions. However, we cannot assume that this tool will work equally well for any discussion topic and any context. As with any Machine Learning algorithm, it requires substantial training data and will need further contextualization for new applications. A system that could perform well for any discussion topic would require an Artificial General Intelligence (AGI) that could understand data related to any topic. Building an AGI remains an unsolved issue in the Computer Science field, and it is expected to remain a challenge in the near future. So far, the system proposed

in this thesis has been tested with data related to (1) renewable energy, and (2) challenges experienced by students in the context of COVID-19, in particular related to online education. Further discussion topics can be explored, provided that sufficient data will be collected from the comments submitted and with some further minor adjustments made to the system.

5. Research Methodology and Design

The research was conducted with a mixed methodology as in any transdisciplinary research. The main phases of the research are presented in Table 1.1.

Table 1.1. Main phases of the research and methodologies applied

| Methodology | |
|--|--|
| Phase 1 (Literature Review) | <ul style="list-style-type: none"> - Conduct an extensive Literature review of MMs - Find appropriate datasets that capture people's opinions - Apply state-of-the-art Natural language processing and understanding techniques and compare them using appropriate evaluation metrics |
| Phase 2 (Framework Development) | <ul style="list-style-type: none"> - Survey and compare existing features of discussion forums - Develop a user-friendly, moderated and engaging tool for online discussions |
| Phase 3 (Data Collection) | <ul style="list-style-type: none"> - Conduct different experiments with Discussoo. In the first experiment, Discussoo is used by IPPG involving teachers discussing online teaching. - In the second experiment Discussoo is used by a group of researchers and local partners working collaboratively on the project related to community energy in Australian rural areas. - In the third experiment Discussoo is used by a university where they have invited students to discuss challenges during Covid time |
| Phase 4 (Eliciting Knowledge from Data) | <ul style="list-style-type: none"> - Analyze recorded information using multiple text analysis algorithms and libraries which leads to extraction of concepts, relations, weights, and interactions. - Apply state-of-the-art sentiment analysis techniques and use statistical analysis to detect polarity (positive/negative) and its variations across various individuals |
| Phase 5 (Mapping) | <ul style="list-style-type: none"> - Develop theoretical and empirical approaches to visualize opinions/concepts as shared MMs. - Explore cognitive maps as a visualization in which nodes represent concepts and edges represent directed causal effects. |

| | |
|------------------------------------|--|
| <p>Phase 6 (Visualisation)</p> | <ul style="list-style-type: none"> - Compare the pros and shortcomings of existing methods/representations for visualizing MM. - Develop interactive features for interaction using various existing JavaScript/Python libraries |
| <p>Phase 7 (Testing)</p> | <ul style="list-style-type: none"> - Test the platform with multiple experiments and employ A/B testing (which is a good tool for testing the process of decision-making in design) to gather and analyse user engagement data for comparing the engagement of interactive computer models (Esteller-Cucala et al., 2020). - A/B testing will generate data on what works and what does not and will enable us to perform incremental improvements to our discussion tool named Discussoo - Identify and investigate the various actors that interact with the visualization and analyze how they incorporate interdependencies and feedback into their thinking. |

Phase 1:

Extensive literature review is conducted to find the gaps and to have a better understanding of the current state of the art. Initially, an appropriate dataset (containing comments) was used, as we did not have any data in the beginning. In order to find algorithms and libraries that could be useful for the platform, we need a dataset.

Phase 2:

The goal of phase 2 is to develop a framework for online discussions. We have initially compared existing discussion forums to find the required or missing features. For the development of the platform, we use a feature-driven methodology which is an incremental and iterative approach to software development. Basically, it is derived from the Agile methodology, but the main focus of this methodology is delivering parts of working software and incorporating the change after each deliverable. The reason for using FDD (Featuredriven development) is that this platform keeps evolving after each research phase. It is easy to integrate these changes using FDD.

Phase 3:

The third phase is about data collection. We used Discussoo in meetings of our centre (PERSWADE) and conducted multiple experiments. In the first experiment, Discussoo is used by the Institute for Public Policy and Governance (IPPG is an interdisciplinary research institute within the University of Technology Sydney), where they involved teachers to discuss the issue while teaching online. In the second experiment, Discussoo is used by a group of researchers and local partners working

collaboratively on a project related to community energy in Australian rural areas. In the third experiment, Discussoo is used by a university where they have invited students to discuss challenges faced by them during Covid time.

Phase 4:

Once we have data in the database, the next phase is to apply multiple concept mining techniques on collected data in order to identify and extract concepts, keywords, links and weights, and sentiment analysis techniques in order to detect the tonality of text (positive, negative or neutral) within each comment. For example, we can define concept variables as an object or noun such as “soil” or “nutrients”; process, such as “erosion” or “evaporation”, or agent, such as “farmer” or “owner”. For concept extraction, we use different methods like ACE (Automatic concept extraction) proposed by Ramirez and Mattmann, (2004). We test various python algorithms and libraries to find out which one works best for us like spaCy (Fantechi et al., 2021), which is a free, open-source library for Natural Language Processing in Python that features models for tagging, parsing, and concept mining as shown in Figure 1.1.

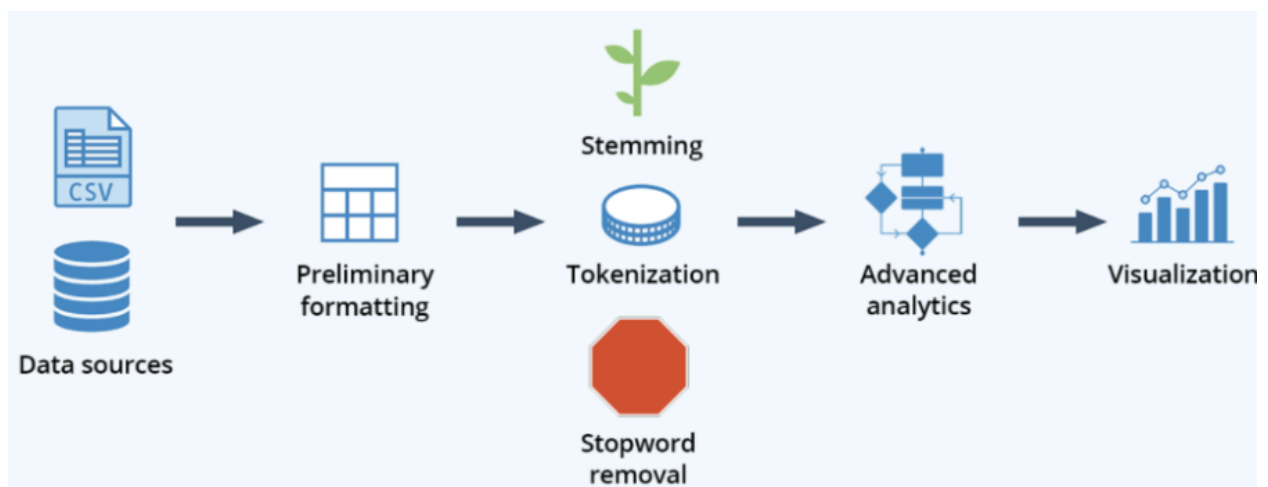


Figure 1.1. Text Analysis phases

Phase 5:

This phase aims to map the extracted elements (nodes, links, weights) to a conceptual model like a concept map. In this phase, theoretical and empirical approaches are developed for translating and assigning opinions/concepts into pre-existing shared MM representations. For example, cognitive maps in which nodes represent concepts and edges represent directed causal effects. Cognitive mapping one

of structured knowledge that is mostly used in social science literature (Gray and Zanre, 2014). We are using cognitive mapping as well for mapping MMs.

Phase 6:

We compare the pros and shortcomings of existing methods/representations for visualizing MMs and have developed interactive features for interaction with FCM using various existing JavaScript/Python libraries.

Phase 7:

We run multiple experiments and employ A/B testing (which is a good tool for testing the user experience) to gather and analyze user engagement data for comparing the engagement of interactive computer models. A/B testing will generate data on what works and what does not, enabling us to incrementally improve Discusoo. We identify and investigate the various actors that interact with the visualization and analyze how they incorporate interdependencies and feedback into their thinking.

6. Outline of the Thesis

The thesis is written in the format of ‘thesis by compilation’ and includes a series of papers allocated to the chapters:

Chapter 1 presents the background and aims behind the research, research goal, objectives, and questions.

Chapter 2 presents a detailed overview of Discusoo: An online discussion framework that can capture representations of a group’s opinion from an online web forum and translates these into semi-quantitative computer models

Chapter 3 present an application of Discusoo as an intelligent tool for multi-scale participatory modeling

Chapter 4 shows a Participatory Methodology for Mapping MMs from Online Discussions

Chapter 5 presents the results of experiments about reconstructing MMs through a moderated framework for serious discussion.

Chapter 6 highlights the main contribution of this research and proposes future directions for research.

7. Note on COVID 19 Impact on this research

This research was conducted during 2019 - 2021, and during the last two years, we all were going unpredictable COVID times. Due to this COVID situation, we had no other choice except to readjust our plans for conducting the experiments according to the COVID situation. Initially, we planned to have focus group experiments with participants by inviting them all to the same venue, but COVID restrictions had changed that plan. Apart from that, we managed to conduct all other experiments online using Discussoo.

Chapter 2: An online, AI-powered, tool for moderating serious discussions and fostering stakeholder engagement

Preamble

Paper Status: Submitted, in review

Authors: M.A., A.V, F.P., F.T.

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Conceptualization: M.A., A.V, F.P., F.T.;

Investigation: M.A., A.V, F.P., F.T.;

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Writing (review and editing): M.A., A.V, F.P., F.T.

1. Overview

In Chapter 2 we are introducing Discussoo as a moderated tool for online and serious discussion. We have established the basis for our research referring to the existing literature. The tool was specifically designed to engage stakeholders and to help them interact in search of solutions to problems. Discussoo has been initially designed to support multi-scale participatory modeling but has been then expanded to handle all sorts of stakeholder engagement, while enriching the process with AI generated content. Users respond or expand on other user's opinions and/or initiate

new lines of discussion. The discussion chain is mined in real-time, using an ensemble of algorithms to extract opinions, keywords, and concepts. This information is transcribed into conceptual models as the discussion evolves. To provide feedback, the system presents users with dynamic visualizations of the collective mental model which they can use as contextual information to refine and update their individual mental models. Feedback can also be introduced by targeted moderator comments to steer or "nudge" the discussion towards a desirable collective mental model, outcome, consensus, or agreement.

The name – Discussoo – was chosen to make it clear that our focus is on discussion support. The ending gives it an Australian flavor, as in ‘kangaroo’.

2. Abstract

With the advent of social media and various online tools, there are more opportunities for meaningful and productive interaction with stakeholders, which can potentially enhance, if not substitute, some parts of in-person engagement. Most existing social platforms (Twitter, Facebook, etc.) have not been designed for serious discussions and with an explicit focus on stakeholder engagement. When improperly used, such platforms operating on a large scale can be even detrimental to productive engagement. This paper presents Discussoo, a tool specifically designed to support multi-scale participatory modeling. The original development has been progressively extended to handle various types of stakeholder engagement while enriching the process with AI-generated content. Users can participate in the discussion by adding a new comment or by responding to others’ comments. The discussion chain is mined in real-time, using an ensemble of algorithms to extract opinions, keywords, and concepts. This information is converted into conceptual models as the discussion evolves. Different gamification elements have been added to the platform to make the discussion more engaging. This framework could be used in a variety of settings and situations where the steering of collective efforts is requested to improve the functioning, resilience, and/or sustainability of a given (social, environmental, or technical) system, or used by policy makers or any other organization who would benefit from a more direct, transparent and meaningful engagement of its stakeholder.

Such a tool can be used in different domains to understand the opinions expressed by stakeholders within a given problem situation.

Keywords: Artificial intelligence, mental models, human behavior, conceptual models, digital communication and interaction, opinion forming.

3. Introduction

Communication tools such as different platforms for discussions (e.g., Bang the table, Pol.is, Kialo, etc), enable interaction and allow taking opinions from users. They are very useful for collective decision-making, as they enable a better understanding of the current dynamics of ideas and policy formation. Web-based communication tools are commonly used for targeting a wider audience as it brings diverse perspectives and more arguments as compared to other methods of discussion. In order to extract some useful insights from these discussions and avoid going off-topic, it is very important to keep the discussion focused. That's why it is very important to have a moderated communication tool where the moderator is involved.

Online discussion forums that are used for citizen deliberation and community engagement require a more cautious approach to the process of discussions (Janssen and Kies, 2005). On the one hand, such online forums can help to address the challenges related to social hierarchies (Wojcik, 2008), and, hence, make the process more open for various groups of stakeholders. On the other hand, the use of such tools can be associated with a range of difficulties leading to undesired and unintended results from public participation. (Wright, 2009) and Lampe et al. (2014) mention polarization of the debates and hostility (flaming, trolling, etc.) as some of the possible challenges that undermine the quality and the purpose of the discussion process. (Kearns et al., 2002) suggest that unstructured discussion can lead to chaos ('free speech without regulation becomes just noise') where the loudest or the most active participant takes over the whole debate.

The participants of online forums can be overwhelmed by the quantity and diversity of arguments and ideas (Lampe et al., 2014). Moderation of online discussions is perceived as one of the effective strategies to manage these issues (Lampe et al., 2014; Wojcik, 2008; Wright, 2009). It can help to overcome information overload and sustain participation, prevent insulting behaviors, and spread of faulty

information reinforced by anonymity (Lampe et al., 2014). Still, there is no versatile answer on the issue of who should take the role of moderator, what this role encompasses, and which qualities are essential to do the job right.

In the context of citizen engagement, there is no agreement on how to choose a moderator for an online forum (Wojcik, 2008). Multiple context-related questions can be asked: (1) whether a moderator should be fully external to ensure his independence and unbiased performance (Wright, 2009), (2) whether they should have expertise in the topic (Wojcik, 2008; Wright, 2009), (3) whether technology can serve the role (Wright, 2009; Young, 2018), and (4) whether the moderator should be chosen by and from the community itself (Noveck, 2004). There is also a diversity of roles that can be taken in orchestrating online discussions. Wright (2009) suggests ten possible roles based on the functions that a person performs: greeter, conversation stimulator, conflict resolver, summarizer of debates, problem solver, supporter, welcomer, cybrarian, open censor, and covert censor. Coleman et al. (2001) propose seven types of activities: social host, team manager, community of practice, cybrarian, help desk, referee, and janitor. Based on empirical research in French municipality forums, Wojcik (2008) distinguished three functions of moderators: manager, referee, and intermediary. Additionally, Wright (2009) suggested that there could be two forms of moderation: human-based content moderation, where no feedback is given to the participants of the forum, and interactive moderation, where the moderator actively engages the participants.

Looking holistically at a discussion dynamic, the moderator definitely plays a critical, if not a key, role. The moderator is expected to maximize the value of a given discussion by encouraging a focused approach to achieve some kind of conclusion, decision, or agreement. Additionally, the moderator is normally responsible to prevent possible unwanted dynamics, including, for instance, hostile discussions. Moderation implies certain risks, such as censorship. In such a context, the moderation model is extremely important. Indeed, while a soft approach can simply make moderation not effective, a too strong approach can lead to lower participation and lack of trust, which eventually undermine the whole process of online discussion (Wright, 2009). Finding the appropriate balance in context can be challenging, requires a certain experience, and can be achieved through defining clear rules.

Lampe et al. (2014) elaborated on the other drawbacks of moderating online discussions. The moderators unintentionally may subjectively rate and respond to the comments according to their own perspectives. Insufficient attention to other messages, e.g., to the ones with the low scores or 'likes', can lead to the loss of important perspective or underrepresentation of some ideas. Lampe et al. (2014) proposed 'meta-moderation' that is about having other moderators who ensure that nothing important was omitted. Most of the researchers agree on the need to moderate discussions on policy-related topics that require stakeholders' involvement (Wright 2009). However, the functions or roles that such a moderator holds should be carefully determined based on the context of the process and consider possible side-effects related to the openness of opinion expression.

(Young, 2018) elaborated on the possible support of technology that should ideally help to substitute, or more realistically limit human moderation. A practical example is the moderation bot, which is resulting to be quite useful for controlling abusive content in a range of possible contexts, including online forums and, more in general, social media. More holistically, given the recent advances in AI, a hybrid or semi-supervised approach is likely to result effectively in practice. The key underlying idea is to have on one side clear technological support to identify potentially unwanted content and, on the other side, the possibility to assess the situation in context and moderate it accordingly.

There are many online and offline tools and forums available for discussion, yet none of them can moderate the ongoing discussion and at the same time analyse the opinions instantly to extract some insights or provide feedback and most of them are not using any gamified approach to make discussions more engaging. So, in order to provide instant constructive feedback to the users about the ongoing discussion, the need of the hour is to have a smart tool for analyzing the discussion text on the fly and eliciting the group opinion/mental model. To our best knowledge, there is no discussion forum that holds modeling functionality or can mimic the modeling process. It is challenging to sustain participants' engagement in such an asynchronous discussion setting.

Addressing the challenges, in this research, we have developed an online moderated forum that captures a group's mental models from an online discussion and translates those into formal models to facilitate communication and

understanding. This web platform, called Discussoo, can capture the opinions of users, in form of concepts, topics, and sentiments attached to those opinions, including the relationships between them by using various natural language processing techniques. These elements are used as building blocks to construct dynamic conceptual models such as word clouds, cognitive maps, conceptual map diagrams, etc. Discussoo allows the moderator (researcher, government agency, or non-profit organization) to extract and analyze cognitive maps that provide relevant and actionable insights about a group's mental model. These can be then fed back into the discussion, informing participants, and helping to produce new and creative solutions to complex and controversial societal issues. In order to sustain participants' engagement in such an asynchronous discussion setting, we have incorporated gamified features into the Discussoo platform.

Discussoo is particularly useful for stakeholder engagement by providing a unified platform to bring together researchers, stakeholders, and decision-makers in the participatory process for better decision making, with no restrictions neither for the size of the group nor for the timing and location of their meetings. Such a platform under supervisory control can pave the way for a plethora of applications in many fields. The framework should provide both users and moderators with the information needed to understand and formalize group's mental models, and in doing so, contribute to producing new and innovative solutions to complex societal problems. The framework of such a proposed model in this article is shown in Figure 2.1.

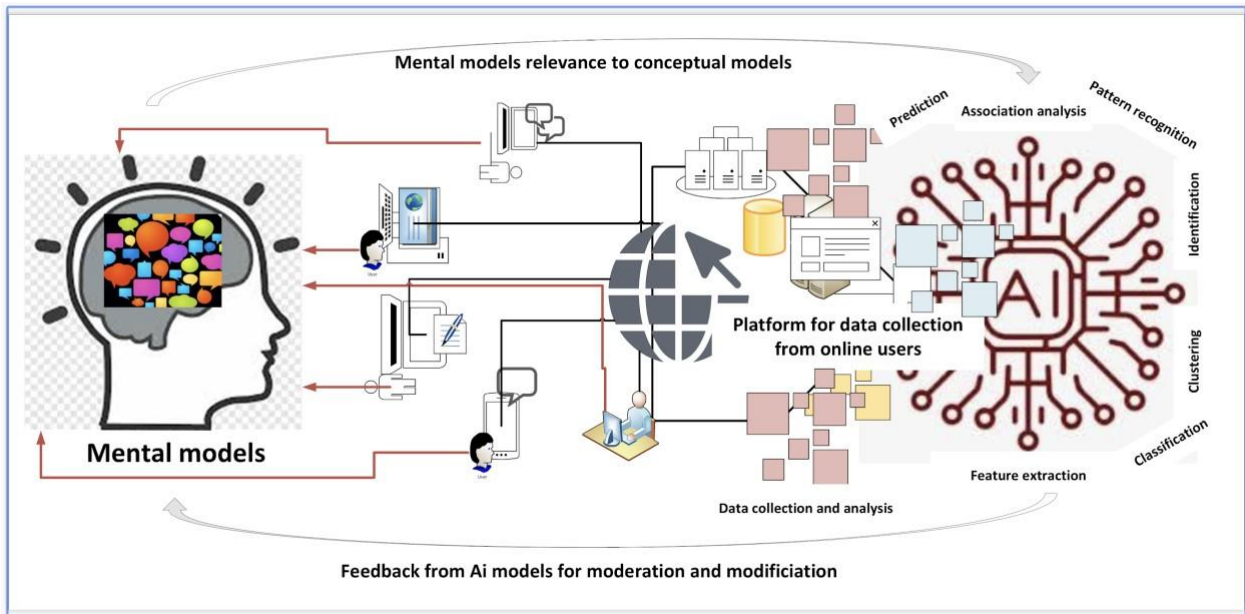


Figure 2.1. Discussoo Framework

The review of existing techniques of text mining for extracting elements needed to create a conceptual model from unstructured data is Section II. Section III presents the detailed overview of Discussoo that includes details about frontend and backend. Section IV presents a range of possible future applications for the proposed system model along with the implementation of the system for specific applications in current sight. Then, Section V discusses the challenges on the way to the development and implementation of AI-assisted tools along with the future research directions and trends. Finally, the conclusions of the paper are presented in Section VI.

4. Review of existing text mining and computational linguistics techniques

Looking at the analysis of discussions in real-time, a literature review has been conducted to provide an overview of existing text mining and computational linguistics techniques (also known as Natural Language Processing (NLP)) shown in Table 1.

Text mining is known as a technique of extracting finest information from text and entails "the automatic extraction of information from several written resources by a computer to discover new, previously undiscovered information". Websites, books, emails, reviews, and articles are examples of written resources. Statistical pattern learning is commonly used to provide high-quality information by generating patterns

and trends. We can distinguish three main views of text mining, according to (Hotho et al., 2005):

Table 2.1. A review of existing text mining and computational linguistics techniques

| Technique | Method | Goal/Aim | Type of output | Type of data | References |
|------------------|------------------------------|--|-----------------------|---------------------|--------------------------------|
| Text Mining | Unsupervised Methods | Presenting a very robust and reliable solution for sentiment analysis | Reviews | Unstructured | (Paltoglou and Thelwall, 2012) |
| | Unigram Model | Sentiment analysis for Twitter data is not that different from sentiment analysis for other genres | Comments | Unstructured | (Agarwal et al., 2011) |
| | Machine Learning | Standard machine learning techniques definitively outperform human-produced baselines | Comments | Unstructured | (Pang et al., 2002) |
| | Unsupervised Methods | Exploiting AI and Semantic Web techniques | Links | Unstructured | (Cambria et al., 2010) |
| | Algorithm and Data Structure | Various disciplines can be more expertly integrated | Reviews | Unstructured | (Calvo et al., 2010) |
| | Clustering Algorithm | Extracting information from different written resources | Reviews | Unstructured | (Cai and Sun, 2009) |
| | Machine Learning | Extracting useful pattern | Concepts | Unstructured | (Hotho et al., 2005) |
| | Algorithm and Data Structure | Bootstrapping techniques for information extraction | Links | Unstructured | (Feldman and Sanger, 2006) |
| | Machine Learning | Creating systems that can process subjective information effectively | Interviews | Unstructured | (Bakshi et al., 2016) |

| | | | | | |
|-----------------------------------|------------------------------|--|----------|--------------|---------------------------|
| Natural Language Processing (NLP) | Clustering Algorithm | Various techniques were specified for grouping/classifying and labelling data | Reviews | Unstructured | (Sinaga and Yang, 2020) |
| | Machine Learning | It can reduce the effort required to analyze the requirements of open-source projects | Concepts | Unstructured | (Vlas and Robinson, 2011) |
| | Machine Learning | Helps to develop a domain model of the document | Links | Unstructured | (Huyck, n.d.) |
| | Algorithm and Data Structure | Achieving humanlike language processing for a range of tasks or applications | Reviews | Unstructured | (Zhang and Liu, 2014) |
| | Clustering Algorithm | Achieving competitive performance in object categorization | Reviews | Unstructured | (Sinaga and Yang, 2020) |
| | Unsupervised Methods | Preprocessing and selecting the important feature with information gain based on entropy | Comments | Unstructured | (Patil and Atique, 2013) |
| | Unsupervised Methods | Selecting features for text classification | Comments | Unstructured | (Shang et al., 2013) |
| | Unigram Model | Provides state-of-the-art word embeddings | Comments | Unstructured | (Goldberg and Levy, 2014) |

information extraction, data mining, and a KDD (Knowledge Discovery in Databases) process (Zhang and Liu, 2014). According to Feldman “text mining is the process of structuring the input text (usually parsing, with the addition of some derived linguistic features and the removal of others, and subsequent insertion into a database), deriving patterns within the structured data, and finally evaluating and interpreting the output” (2006). Document is seen as a textual data unit that can be found in a variety of collections (Vinayavekhin et al., 2021). Text mining techniques are used by scientists to organize large amounts of text data (i.e., to solve the issue and problems linked with unstructured data), and to recognize and detect the opinions shared through text e.g., sentiment analysis in social media (Feldman and Sanger, 2006; Hotho et al., 2005). Sentiment analysis may entail analyzing movie reviews to determine how favorable a review is for a particular film (Feldman and Sanger, 2006). A tagged data collection or affectivity tagging of words may be required for such an analysis. WordNet and ConceptNet (Son et al., 2020) contain resources for the affectivity of words and concepts. In the related field of emotional computing text has been utilized to detect emotions (Pang and Lee, 2008).

Affective computing systems based on text have been applied to a variety of datasets, including student assessments, children's stories, and news reports. In the past, most websites relied on text-based searches, which only returned output/results that contained certain terms or phrases entered by the user. Text mining can find content based on meaning and context thanks to the deployment of a semantic web (rather than just by a specific word) (Paltoglou and Thelwall, 2012). Text mining tools can also be used to compile huge records of data about various individuals and occasions. Large datasets can be constructed based on data taken from multiple sources, e.g., news, and these datasets help in social network analysis or counterintelligence. Text mining software can function similarly to an intelligence analyst or a research librarian, albeit with a narrower scope of the study. Some email spam filters use text mining to identify the features of messages that are likely to be ads or other unwelcome content.

Text mining research currently focuses on issues such as text representation, categorization, clustering, information extraction, and the discovery and modeling of hidden patterns. The selection of qualities, as well as the influence of domain expertise and domain specific techniques, are critical in this context. As a result, text data frequently necessitates the adaption of well-known data mining algorithms. To do so,

researchers in the fields of information retrieval, natural language processing, and information extraction usually rely on their expertise and findings.

The algorithms related to the traditional method are the following:

- 1- Bag-of-Words (BOW): list of words and number of occurrences of these words in the sentences (Qader et al., 2019). In this approach, the number of relevant keywords (words, stems, n-grams) are mined from a training dataset. A binary vector can be used to represent a text, with the elements indicating the presence or nonexistence of a relevant term within the text. Real-numbered vectors, on the other hand, can be employed where each component indicates the frequency of the term within the dataset (Kalyan and Sangeetha, 2020).
- 2- N-grams: An n-gram is an adjacent categorization of 'n items' from a given text or speech. Two types of n-grams from different "item" definitions are letter and word.
- 3- Part of Speech Tags: A technique to tag every word based on grammar.

Furthermore, word embedding methods are widely utilized in text representation where words in a vocabulary are changed to continuous real-number vectors. Word2Vec (Mikolov et al., 2013) uses Neural Networks, and GloVe (Vlas and Robinson, 2011) uses matrix factorization and these two are the widely applied methods for learning word embeddings. When it comes to word embedding approaches, however, there are two major drawbacks. First, to create appropriate feature representation models, a large number of training documents are required at the beginning. Second, because of their generality, some pre-trained models (most of those models are trained using Wikipedia data) may not be appropriate for certain sentiment categorization settings. For these reasons, a BOW representation was used in this study, with the Term Frequency–Inverse Document Frequency (TF–IDF) index used to extract the value of each feature (Alzayed and AlHunaiyyan, 2021).

Classic machine learning models are still widely employed for sentiment categorization when it comes to classification algorithms. Support Vector Machines (SVMs) have lately been implemented in multiple applications of sentiment analysis, including assessing the information's quality in product reviews (Zhang et al., 2010), observing the human papillomavirus vaccination sentiment trend from tweets (Patil and Atique, 2013) for detecting polarity i.e. positive, negative, and neutral tweets (Shang et al., 2013). In addition, Naive Bayes (NB) classifiers are also extensively implemented as Goldberg and Levy (2014) proposed an emotion recognition

framework that was based on multiple classifiers. Pennington et al., (2014) used an NB classifier along with a Maximum Entropy learner, a knowledge-based technology that does a deep analysis of natural language sentences combined with a voting mechanism to classify emotions. The authors demonstrate how this ensembled model extracts sentences from a variety of sources, including news headlines, news articles, and Twitter posts. The results demonstrate that among the three parts of the ensemble, the NB classifiers, which use a BOW text representation, obtain maximum accuracy.

NLP is particularly effective in the realm of requirements engineering (RE). RE is the first step of the software development life cycle and is an important element of software engineering. It entails several steps, including elicitation, analysis, documentation, validation, and requirement management (Agarwal et al., 2011). RE is a time-consuming and error-prone process, especially when dealing with big data [29]. The RE process lays out all of the conditions that must be met for a new system to be successful. Furthermore, the RE process gathers the necessary and suitable domain knowledge, which includes the stakeholders' requirements (customers, end-users, domain experts). To achieve this purpose, the requirements elicitation and requirements analysis procedures are completed incrementally and iteratively. Both informal natural language (NL) and formal modeling language are used in these activities. NL is the global format language that all end-users and stakeholders across all disciplines can understand (Cambria et al., 2010). However, NL might be unclear, resulting in misunderstandings about requirement definitions. By developing appropriate RE specification papers, NLP can improve communication between requirement engineers and domain experts (i.e., users). NLP can also help computers interpret human-written natural language material. NLP algorithms are divided into two main categories, traditional and deep learning as shown in Figure 2.2.

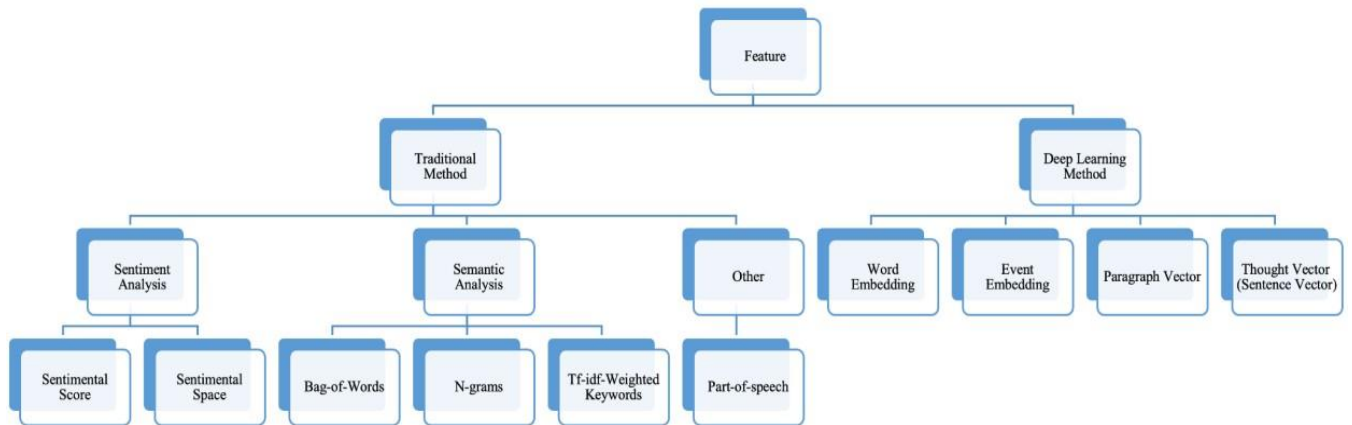


Figure 2.2. Categories of NLP algorithm (source: self-elaboration based on literature)

It is worth noting that deep learning-based approaches have been utilized for sentiment analysis (Li and Li, 2013). Most of these methods merely use a word embedding text representation with some convolutional/recurrent neural network layers on its tops (Du et al., 2017; Tellez et al., 2017). The challenges in using NLP for analysing social media data are presented in Figure 2.3.

Challenges and difficulty in using NLP in social networks and media:

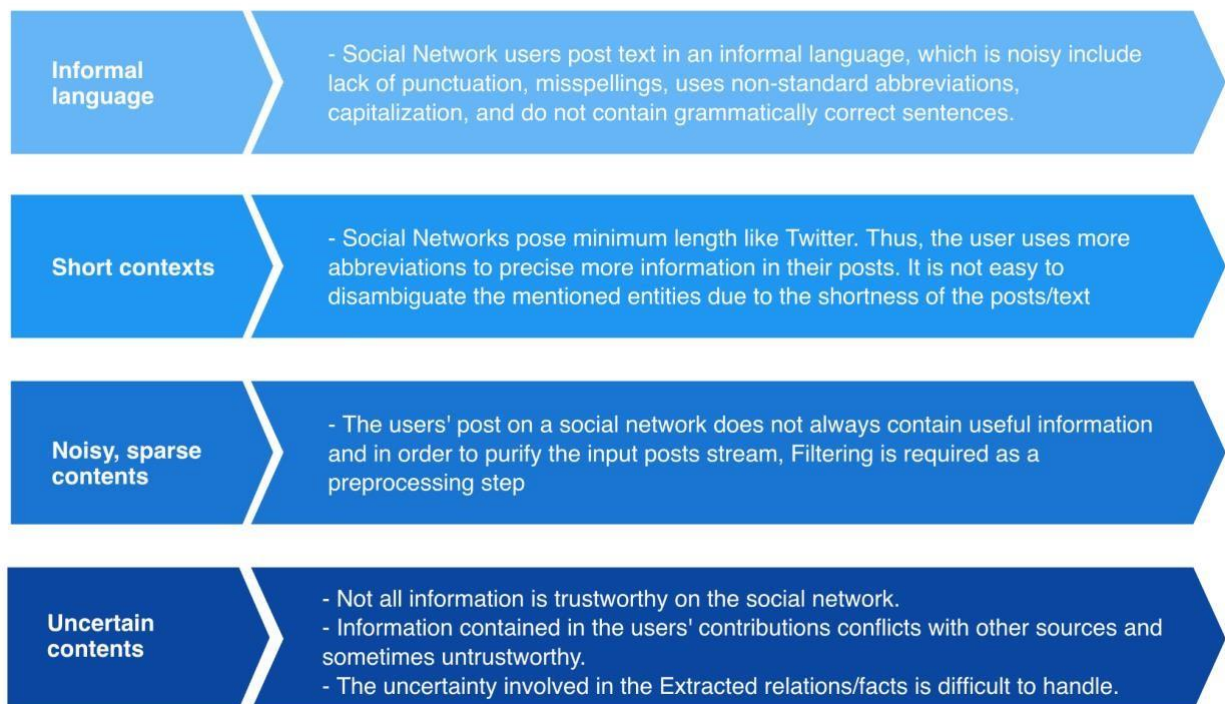


Figure 2.3. Challenges in using NLP (source: self-elaboration based on literature)

The purpose of this literature review is to compare and analyze existing text mining and computational linguistics techniques and identify those that can be best used for eliciting the building blocks of mental models. These elements include concepts, topics, opinions, sentiments, and others from unstructured data that is in the form of comments.

Humans develop mental models on the notion of "truth" to lessen the strain on our working memory even more (Biggs et al., 2011). The concept of truth mandates that mental models only reflect valid premise propositions and ignore false ones, i.e., they adhere to the closed world assumption. When faced with the exclusive disjunction "I can either go on vacation or finish the project I'm working on," humans would construct two mental models based on the principle of truth: "I go on vacation" and "I finish my project." Each model excludes the falsification of the other premise. We could interpret it as "I go on vacation and don't finish my project" and "I don't go on vacation and finish my project" if we were more exact and built the entire model. However, our brains' shortcut leads to predictable deduction errors, which we don't want to replicate with neural networks. After reviewing existing text mining and computational linguistics techniques, those approaches which are most suited for eliciting the building blocks of mental models/users' opinions (concepts, topics, opinions, sentiments, etc. from a discussion platform) are shortlisted and tested in Discussoo.

5. An online AI-Based Tool for serious discussion: Discussoo

Discussoo is an online forum that gives the participants a holistic view of the problem being discussed. Many software engineers and researchers have chased the elusive goal of getting meaningful results from unstructured data. Discussoo allows users to participate in discussions by adding their comments. It uses different text analysis techniques to extract concepts from the comments and create a visual mind map of each discussion in real-time.

Another challenge in online discussion platforms is how to sustain people's motivation about a topic under investigation, so we introduced game design elements like rating comments and a chatbot in Discussoo to solve it.

5.1. Main features and user functionalities

Discussoo is an online platform for serious discussions. All the features required for a discussion forum (e.g., ability to create private or public discussion, allowing users to participate in the discussion anonymously, introducing a moderator in the discussion, etc.) have been implemented in it.

When users visit the platform, they can review the already available public discussion by joining the platform. Figure 2.4 shows the landing page and discussion page of the Discussoo platform.

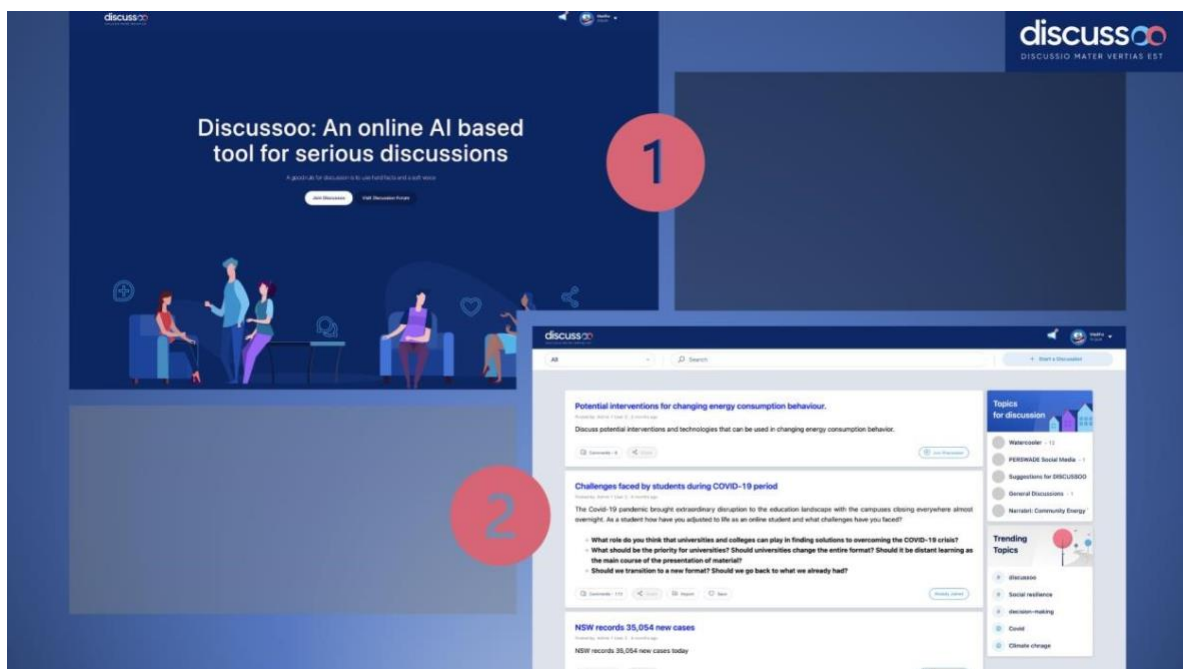


Figure 2.4. Users can get involved in the discussions by pressing the join button

Once users join the platform by registering themselves, they can add their comments, respond to and rate the comments of others and see in which direction the discussion themes are emerging with the help of a real-time mind map (Figure 2.4). Each discussion/post opens a new page where users can contribute to the discussion by leaving comments.

In order to make the discussions more effective and meaningful, users can be assigned different roles e.g. (Admin, Moderator, Group Moderator, Normal User, and Registered User)

5.2. Admin/Moderator Rights in Discussoo

Below are the rights and features provided in Discussoo for moderator and admin.

- **Approving a Discussion:** Any user can create a new discussion in Discussoo. When a user creates a new discussion, it needs to be approved by the admin first. Once the Discussion is approved by the admin it appears on the home page.
- **Editing an Existing Discussion:** Admins/moderators can edit all the discussions.
- **Deleting an Existing Discussion:** Admins can delete any discussion.

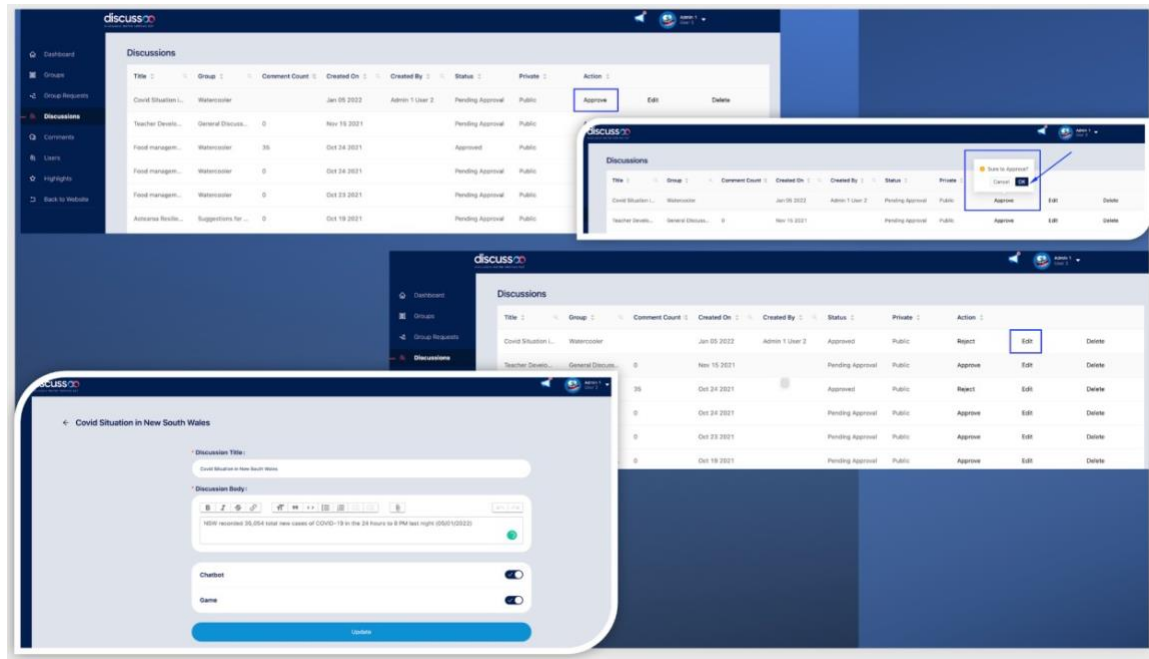


Figure 2.5. Admin can approve/edit/delete discussions in Discussoo

- **Sorting the Discussions:** Admins can sort out the discussion based on title, group, comment count, created on date, status, and actions

- **Rearranging the Discussions in a group:** Admins can bring any discussion/pin on the top in a group. They can use drag and drop functionality for rearranging the discussion (Figure 2.6).

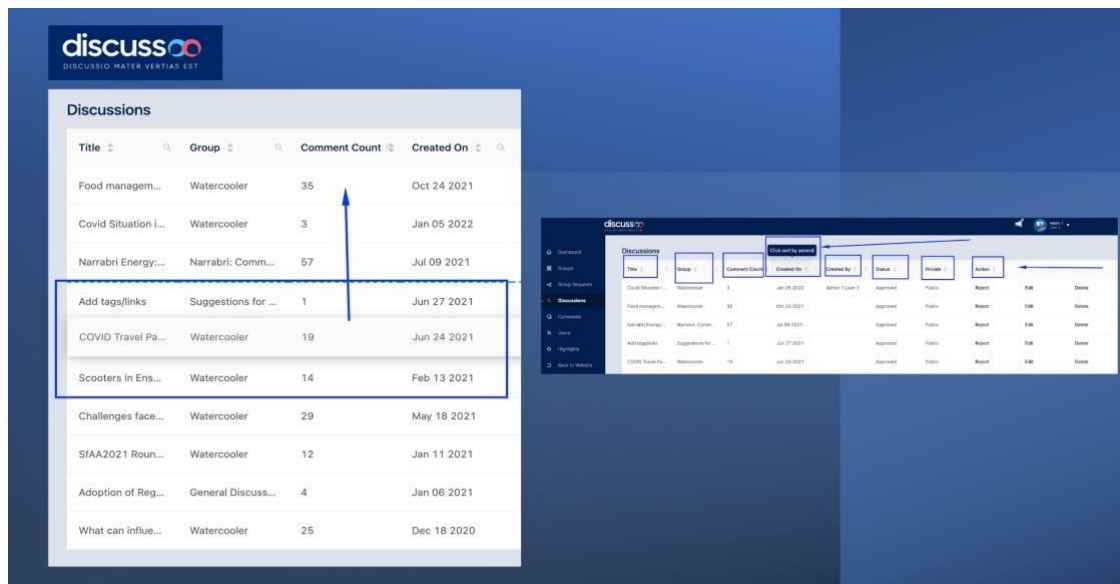


Figure 2.0.6. Admin can sort discussions based on title, group, comment count, and date created in Discussoo. Admin can also rearrange/pin discussion by using drag and drop features

- **Unable/Disable Chatbot and Game in a Discussion:** In Discussoo chatbot and a small game have been added to make the discussion more engaging and interactive. Admins can enable or disable the chatbot and the game in all the discussions. (Figure 2.7).
- **Creating/Editing/Deleting Group:** In Discussoo there is an option of having a private or public discussion. For private discussion, the admin can create separate new groups, edit all the existing groups, and change the group icon, name, descriptions, and moderators (Figure 2.8).
- **Enable/Disable features in a Group:** For each discussion, users can add their comments, users can respond to others' comments, rate/score their comments, and share discussions to other social media platforms. Admins can enable and disable the following features in any discussion.
 1. Reply
 2. Score
 3. Sharing (Figure 2.9)

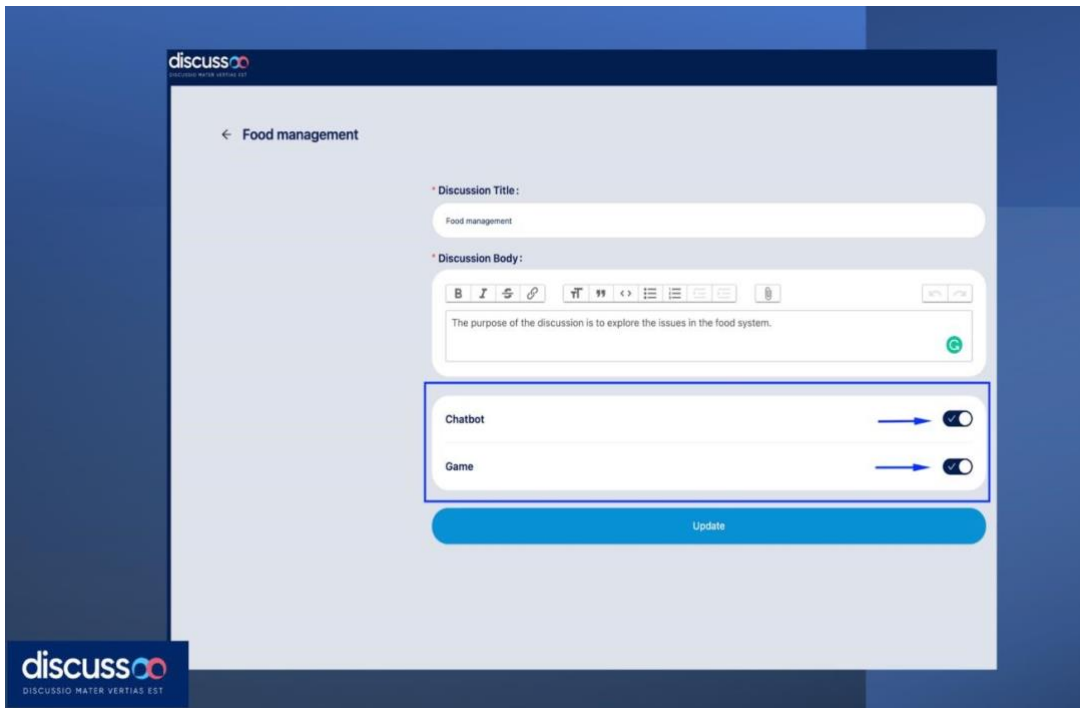


Figure 2.7. Admins can enable or disable the chatbot and the game in all the discussions

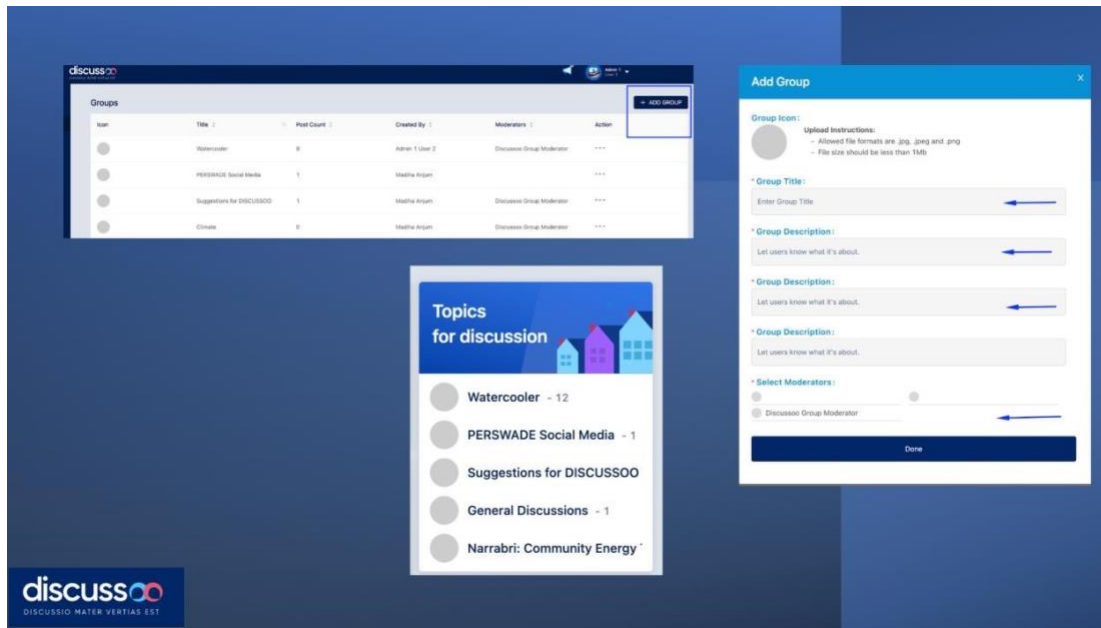


Figure 2.8. Creating/Editing/Deleting Groups in Discussoo

- **Add New User and Edit/Delete Existing Users:** Admin can create new users on the platform. Once Admin creates a new user, the user will receive his credentials (username and passwords) for Discusoo at his email address. Admin can Edit/Delete the existing users on the platform (Figure 2.10). All the users will be added to the Watercooler group by default as it is a public group. Admin can add users to private groups later if requested.

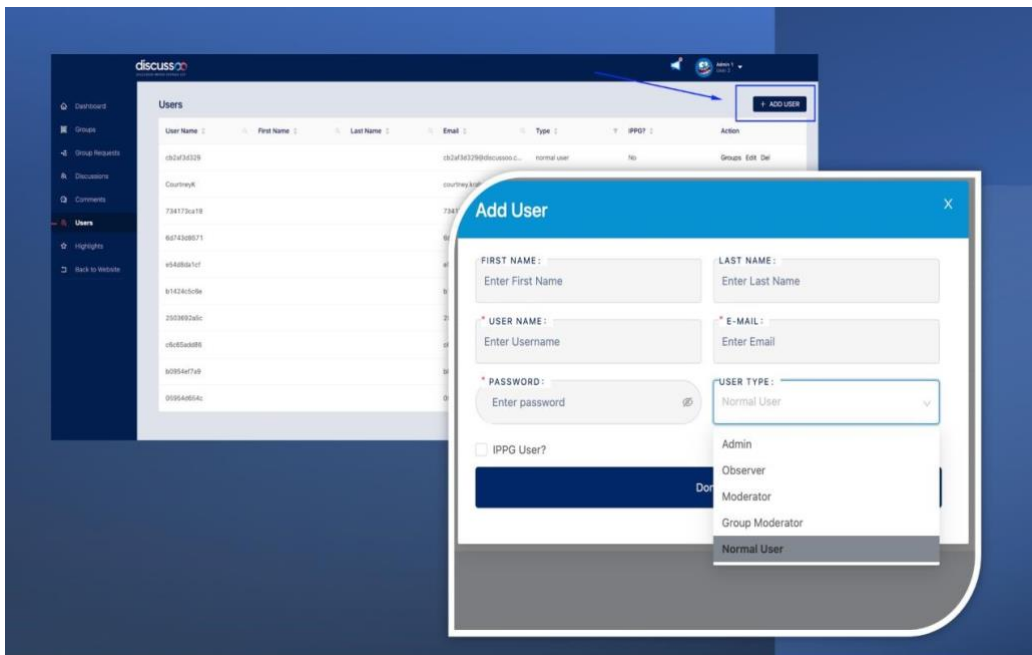


Figure 2.9. Admins can enable and disable the following features in any discussion. (Reply, Score, Sharing)

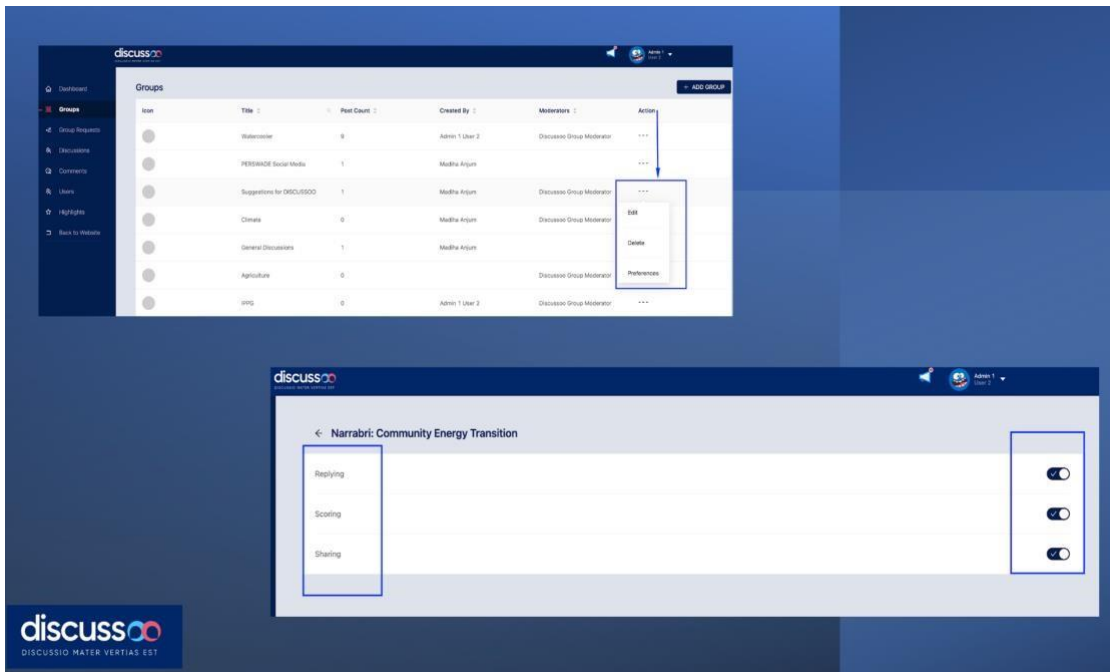


Figure 2.10. Admin can create new users on the platform

- **Adding Trending topics to the Homepage of Discussoo:** Admin can add trending topics to the home page (Figure 2.11)

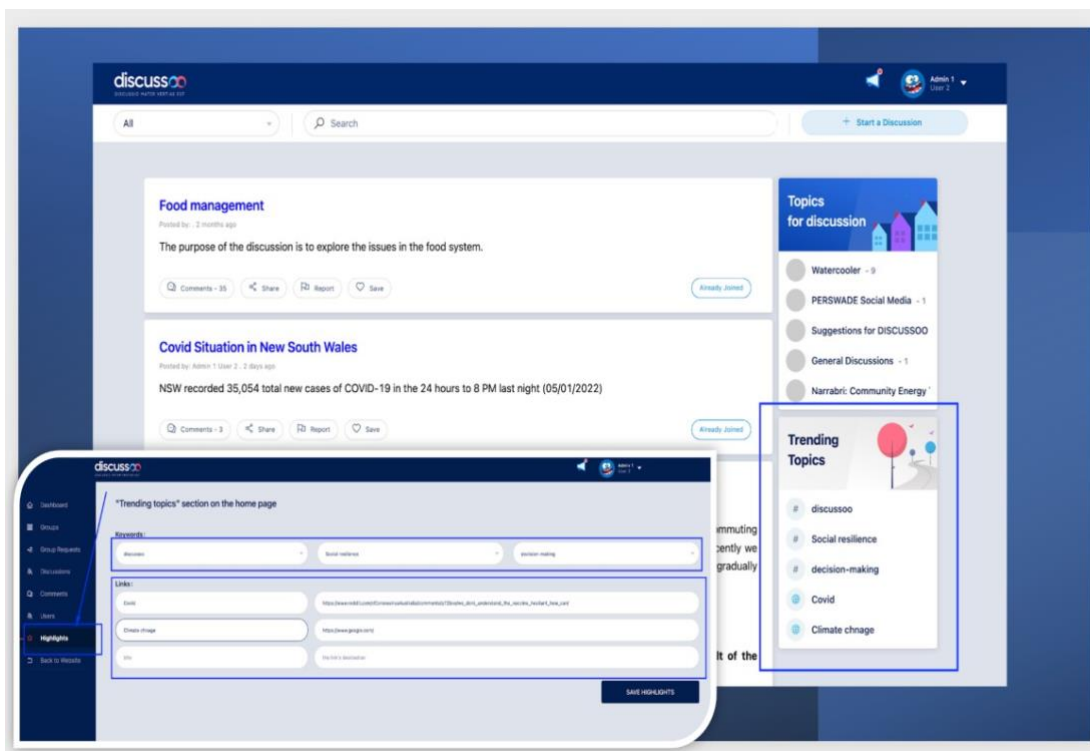


Figure 2.11. Admin can add trending topics to the home page

- **Rearranging the Comments:** Admin/moderator can rearrange all the comments in the discussion, moving them up or down (Figure 2.12).

Using this content control mechanism, moderators can protect the integrity of the topics and discussions. Moderators can encourage lively debates and stimulate the process by making it more enriching for all the participants.

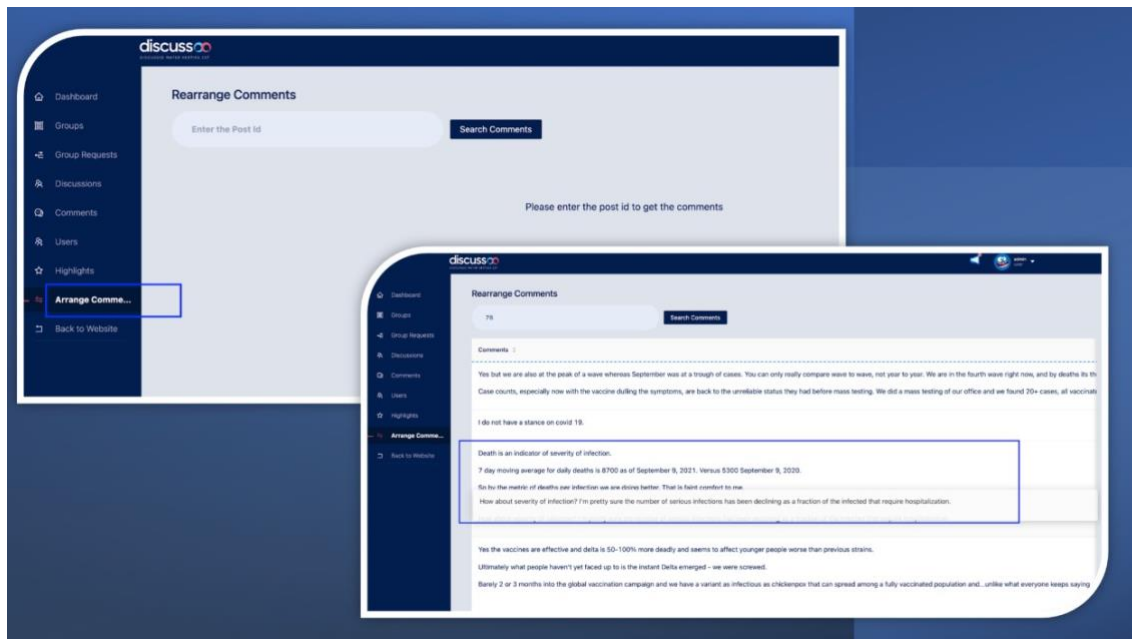


Figure 2.12. Rearranging the Comments

- **Action against Reported comments:** Users can report all the irrelevant comments, and the admin can act accordingly (Figure 2.13).

| Text | Post Title | Group Title | Reported Count | Created On | Created By | Rating | Action |
|--------------------------|-------------------------|-------------|----------------|-------------|------------|--------|-------------|
| <p>how about the cro... | How bad will climate... | Watercooler | 1 | Dec 23 2021 | | 0 | Edit Delete |
| <p><span style="colo... | How bad will climate... | Watercooler | 1 | Dec 14 2021 | admin user | 0 | Edit Delete |
| yeah | How bad will climate... | Watercooler | 1 | Nov 18 2021 | admin user | 0 | Edit Delete |
| <p>yeah you are right... | Testing | Watercooler | 1 | Nov 11 2021 | admin user | 0 | Edit Delete |
| <p><span style="bac... | We don't understand ... | Watercooler | 1 | Oct 20 2021 | admin user | 0 | Edit Delete |
| post about this comm... | Testing editor | Watercooler | 1 | Nov 06 2020 | | 6.3 | Edit Delete |
| Email notifications. | Testing editor | Watercooler | 1 | Nov 06 2020 | Smile Cat | 8.3 | Edit Delete |
| <p><span style="colo... | Covid Situation in N... | Watercooler | 0 | Jan 06 2022 | admin user | 0 | Edit Delete |
| <p><span style="colo... | Covid Situation in N... | Watercooler | 0 | Jan 06 2022 | admin user | 0 | Edit Delete |
| <p>I used to drive my... | Covid Situation in N... | Watercooler | 0 | Jan 06 2022 | admin user | 0 | Edit Delete |

Figure 2.13. Admin can act against reported comments

Using this content control mechanism, moderators can protect the integrity of the topics and discussions. Moderators can encourage lively debates and stimulate the process by making it more enriching for all the participants.

6. Discussoo Engine (real-time analysis of discussions)

In addition to tracking the exchange of comments, Discussoo has a back end, which uses AI techniques to extract new knowledge from the ongoing discussions and improve understanding of problems by generating formal conceptual models from the information provided by users.

In Discussoo all the communication is in the form of text. Users can participate in ongoing discussions by adding their comments and those comments are analyzed in realtime using an ensemble of different algorithms with the goal of generating a formal conceptual model from those discussions. Figure 2.14 shows conceptual framework of Discussoo and Figure 2.15 shows the phases that are involved in the creation of conceptual models from the discussion.

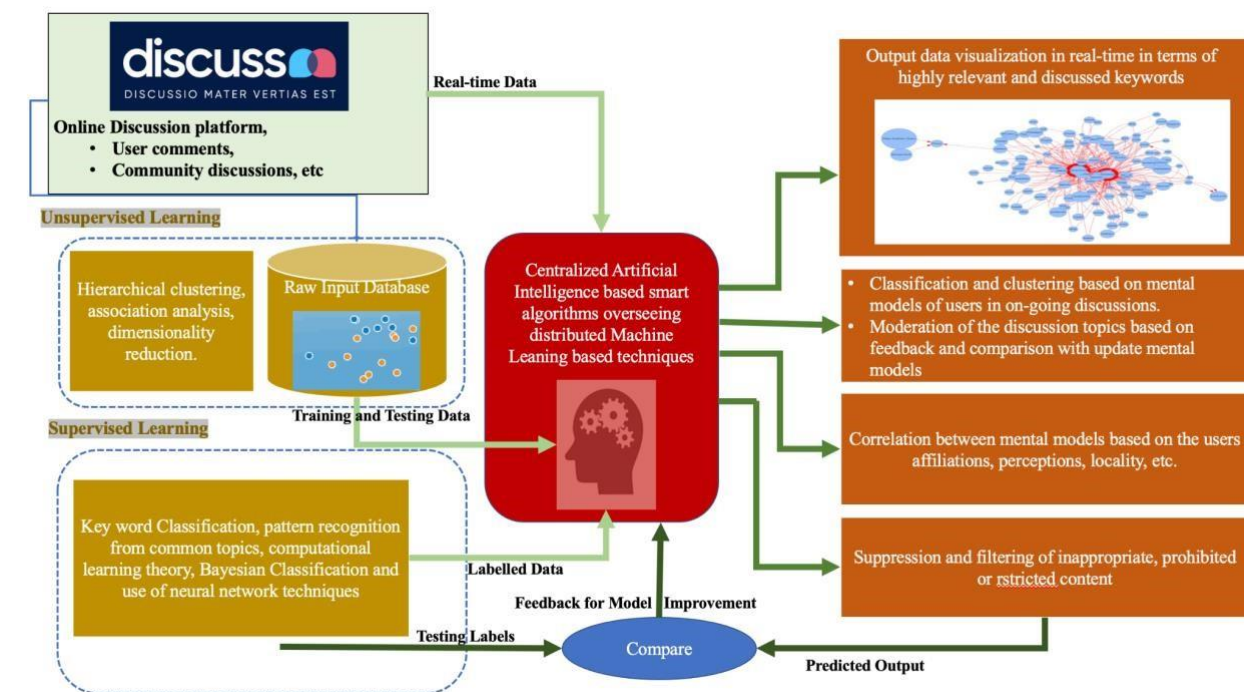


Figure 2.14. Conceptual framework of Discussoo

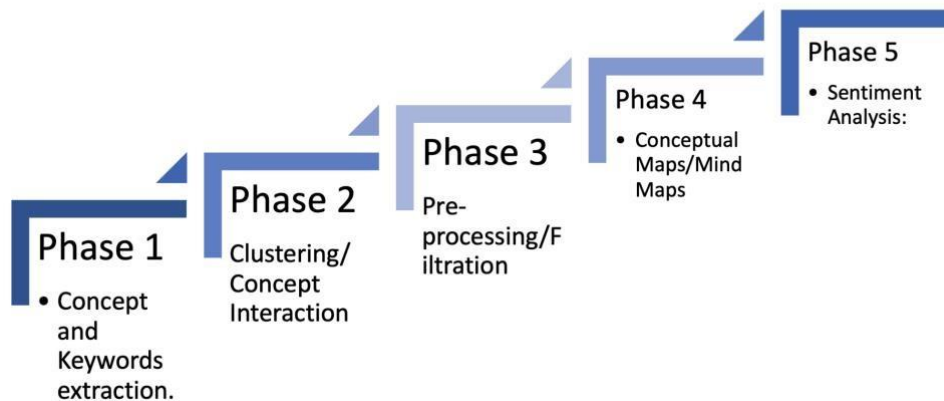



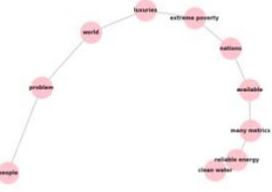
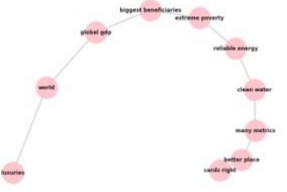
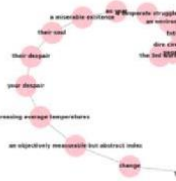
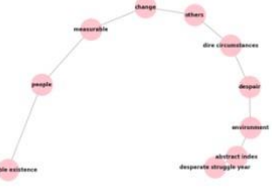
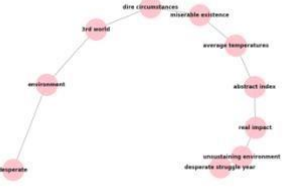
Figure 2.15. Five phases that are involved in the creation of conceptual models from the discussion

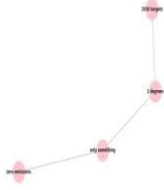
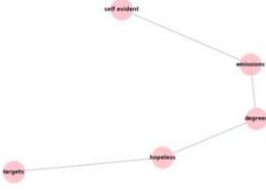
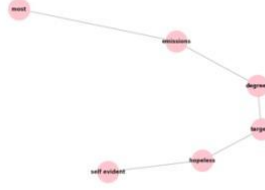
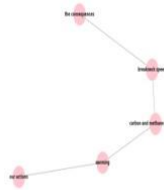
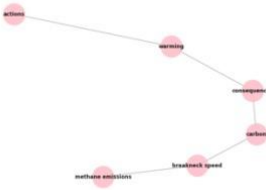
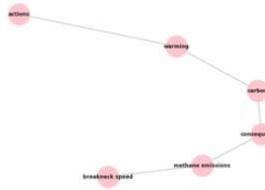
Phase 1: Concept and Keywords extraction

The first step is to identify and test the technique for extracting keywords and concepts from the discussions. Table 2.3 shows test results of Concept/Keyphrase Extraction using techniques like Tf-idf (term frequency–inverse document frequency) (Rajaraman, Ullman, 2011), TopicRank (<https://pypi.org/project/topicrankpy/>), and TextRank (Mihalcea and Tarau, 2004).

Table 2.2. Test results of Concept/ Keyphrase Extraction of bigrams or trigrams instead of unigrams (i.e., concept phrase (2-3 words) instead of concept word) using techniques like Tfidf, TopicRank, and TextRank

| Exp N | Comment | Tfidf | TopicRank | TextRank |
|-------|--|-------|------------|------------|
| 1 | Okay? So what does that mean. Do we need to be to 0 by 2040? Or is it completely hopeless? | - | 'hopeless' | 'hopeless' |

| | | | | |
|-----------------|--|--|---|---|
| <p>2</p> | <p>Global GDP is projected to more than double by 2050 and the biggest beneficiaries of this will be developing nations. Extreme poverty could be entirely eradicated if the will to continue to address the problem continues. Reliable energy and clean water will be available to the nearly one billion people who currently do not have those luxuries.</p> |  |  |  |
| | | <p>Global GDP, the biggest beneficiaries, developing nations, extreme poverty, the will, the problem, reliable energy, clean water, the nearly one billion</p> | <p>'clean water', 'reliable energy', 'many metrics', 'available', 'nations', 'extreme poverty', 'luxuries', 'world', 'problem', 'people'</p> | <p>'cards right', 'better place', 'many metrics', 'clean water', 'reliable energy', 'extreme poverty', 'biggest beneficiaries', 'global gdp', 'world', 'luxuries'</p> |
| <p>3</p> | <p>Having lived in the 3rd world and seen people in dire circumstances. Extinction is not what you should be worrying about. To live in an environment that is so hostile you have nothing but a desperate struggle year in and year out to scrape a miserable existence surrounded by others equally desperate and some who have lost their soul and will escape their despair by feeding off your despair.</p> |  |  |  |
| | | <p>the 3rd world, people, dire circumstances, extinction, an environment, a desperate struggle, and year, a miserable existence, their soul, their despair, your despair, increasing average</p> | <p>'desperate struggle year', 'unsustaining environment', 'real impact', 'abstract index', 'average temperatures', 'miserable existence', 'dire circumstances', '3rd world', 'environment', 'desperate'</p> | <p>'desperate struggle year', 'abstract index', 'environment', 'despair', 'dire circumstances', 'others', 'change', 'measurable', 'people', 'miserable existence'</p> |

| | | | | |
|-----------------|---|--|---|---|
| <p>4</p> | <p>It would seem pretty self-evident from most of what I've read that if zero emissions is only something we intend to reach by 2050 then we can absolutely forget about staying under 2 degrees. 2050 targets are hopeless</p> |  |  |  |
| | | <p>zero emissions, only something, 2 degrees, 2050 targets</p> | <p>'targets', 'hopeless', 'degrees', 'emissions', 'self-evident'</p> | <p>'self-evident', 'hopeless', 'targets', 'degrees', 'emissions', 'most'</p> |
| <p>5</p> | <p>Depends on our actions over the coming decades. If we reduce emissions to zero as soon as possible then we will (mostly) stabilise Earth's temperature and avoid worsening the impacts. If we continue to emit then things will obviously get worse.</p> |  |  |  |
| | | <p>our actions, warming, carbon and methane emissions, breakneck speed, the consequences</p> | <p>'methane emissions', 'breakneck speed', 'carbon', 'consequences', 'warming', 'actions'</p> | <p>'breakneck speed', 'methane emissions', 'consequences', 'carbon', 'warming', 'actions'</p> |

Phase 2: Clustering

After the concept extraction, now the target was to cluster relevant concepts and then assign a representative topic to each of the clusters formed. Some experiments were designed and conducted in this regard to find the best possible solution, the details of which are as follows.

1. LDA

Latent Dirichlet Allocation (LDA) is a topic modeling technique in NLP that is quite popular. However, some issues were observed with the use of this algorithm:

- Not suitable for small-sized text artifacts.
- Stemming and lemmatization affect word structures.

- Only clusters, do not cater to the topic assignment.
- Cluster formation required improvement.

2. K-Means Clustering

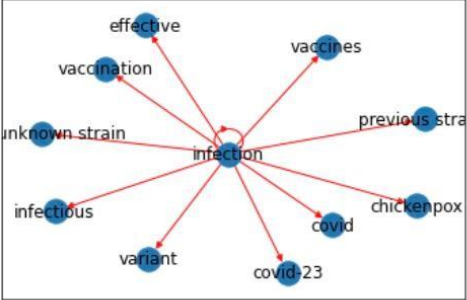
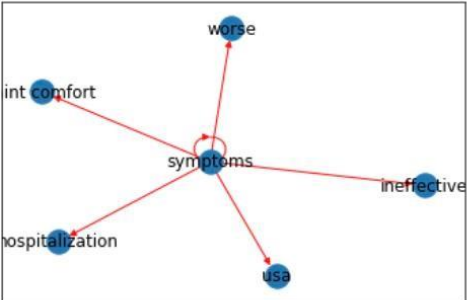
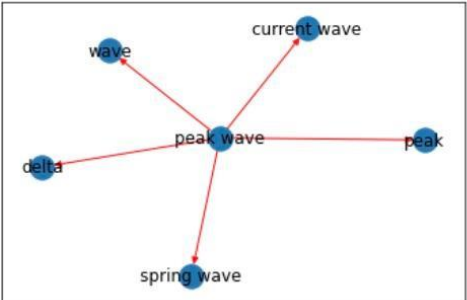
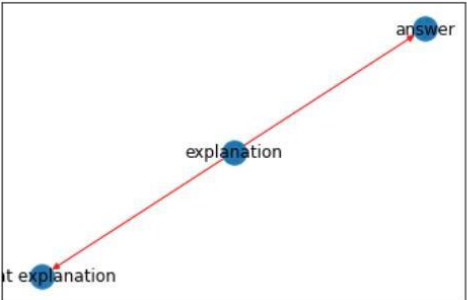
K-means clustering is another clustering technique that is limited to merely a grouping of the concepts and does not cater to the topic assignment. Although the results of K-means clustering were better than LDA based on our experiment, there were still some limitations:

- Determining the ideal number of clusters.
- Repetition of words within the clusters.
- Cluster topics had to be calculated separately.

3. Truncated SVD

Singular Value Decomposition (SVD) is dimensionality reduction algorithm that helps derive topics from the main text. It is different from concept extraction since it is an abstractive approach that retrieves the generic gist from the text artifacts. This algorithm was used to generate topics from the post text and comments which were further used for the clustering of the concepts extracted. The clustering is based on the semantic similarity of the concepts. Table 2.4 shows test results of Clusters and their key phrases extracted using techniques like LDA.

Table 2.3. Results for extracting clusters (Grouping of related words into clusters along with assignment of a topic to each cluster)

| Ex p no. | Cluster | Key-Phrases | Visualization |
|----------|-------------|---|--|
| 1. | Infection | 'covid', 'vaccination', 'effective', 'covid-23', 'vaccines', 'new unknown strain', 'infectious', 'variant', 'infection', 'chickenpox', 'previous strains' |  <p>A network visualization for the 'Infection' cluster. The central node is 'infection', which is connected to several other nodes: 'effective', 'vaccination', 'unknown strain', 'infectious', 'variant', 'covid', 'covid-23', 'chickenpox', 'previous strains', and 'vaccines'.</p> |
| 2 | Symptoms | 'hospitalization', 'worse', 'symptoms', 'ineffective', 'usa', 'faint comfort' |  <p>A network visualization for the 'Symptoms' cluster. The central node is 'symptoms', which is connected to five other nodes: 'worse', 'ineffective', 'usa', 'hospitalization', and 'faint comfort'.</p> |
| 3 | Peak Wave | current wave', 'spring wave', 'wave', 'peak', 'delta' |  <p>A network visualization for the 'Peak Wave' cluster. The central node is 'peak wave', which is connected to five other nodes: 'current wave', 'peak', 'spring wave', 'delta', and 'wave'.</p> |
| 4 | Explanation | 'great explanation', 'answer' |  <p>A network visualization for the 'Explanation' cluster. The central node is 'explanation', which is connected to two other nodes: 'great explanation' and 'answer'.</p> |

Phase 3: Pre-processing

The clusters obtained and labelled are closer in terms of semantics. However, there is still room for improvement which can be achieved by tightening the concept selection criteria. In the next step we will use pre- and postprocessing techniques to filter the cluster topics and concepts to produce a conceptual model.

Here are some of the techniques that were tested out in this regard:

- **Stopword Removal:**

Removing generic words that are not quite meaningful and are required just to maintain the structural integrity of the text. However, in our case, stopwords removal does not serve a lot of purposes because:

- The algorithm already filters stopwords during the keyphrase candidate selection.

- The same is the case with punctuation removal, the key phrase extractor handles it by default.

- **Parts of Speech (POS) Tag Filtration:**

There are certain POSs that do not add much value to key phrases/concepts. These sometimes make it to the selected key phrases. Some examples include Superlative and Comparative adjectives and adverbs. In order to handle their filtration, the Natural Language Toolkit (NLTK) library (<https://www.nltk.org/>) was utilized, the concepts were tagged, and the unwanted ones were filtered out.

- **Entity Filtration:**

Filtering out the entities that are generic and do not add to meaningful concept candidates. The two main entity categories that have been filtered out in this cycle are the DATE and TIME entities. (This can be further refined by going over more data, e.g., filtering names of persons and locations etc.)

- **Subset Removal:**

Removing subset concepts to enhance the uniqueness of the clusters and concepts and reduce redundancy. For instance, “new movies” and “movies” are subsets of each other and can be considered the same.

- **Plural Removal:**

Again, aimed at reducing repetition and redundancy in the key phrases/concepts. For example, ‘days’ and ‘day’ are plural removal cases.

- Perfect Match Removal:

In case the cluster topic and any of the key phrases within the clusters are a perfect match, the concept is removed from the cluster to enhance the significance of the cluster topic.

Phase 4: Conceptual model

Once the concepts and topics had been filtered and cleaned out, we can now move on towards the causal loop diagram (CLD) construction. The main topics of the post are extracted and used as the topics, each of the topics further has related concepts clustered within. The topics themselves are connected to depict a unified relationship (belonging to the same post). Figure 16a shows the conceptual map created in first stage. The visualization is overlapping and appears messy. The reason of adding this figure is to show the complications of this task. This output is further refined to get a meaningful conceptual model. So far, we were not able to fully automate this process and produce meaningful CLDs using AI only. The moderator will have to interfere in the process to validate the produced models and choose the appropriate level of detail. Figure 2.16b shows a filtered conceptual map.

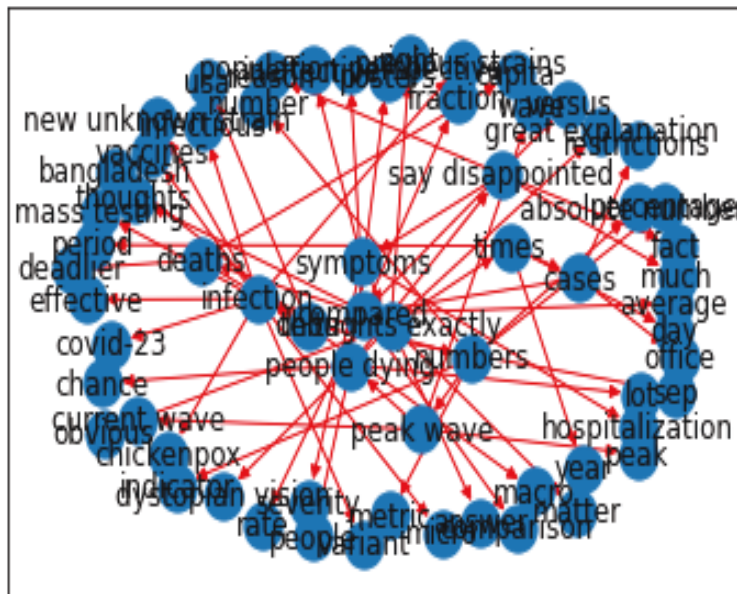


Figure 2.16a. Unfiltered Conceptual Diagram

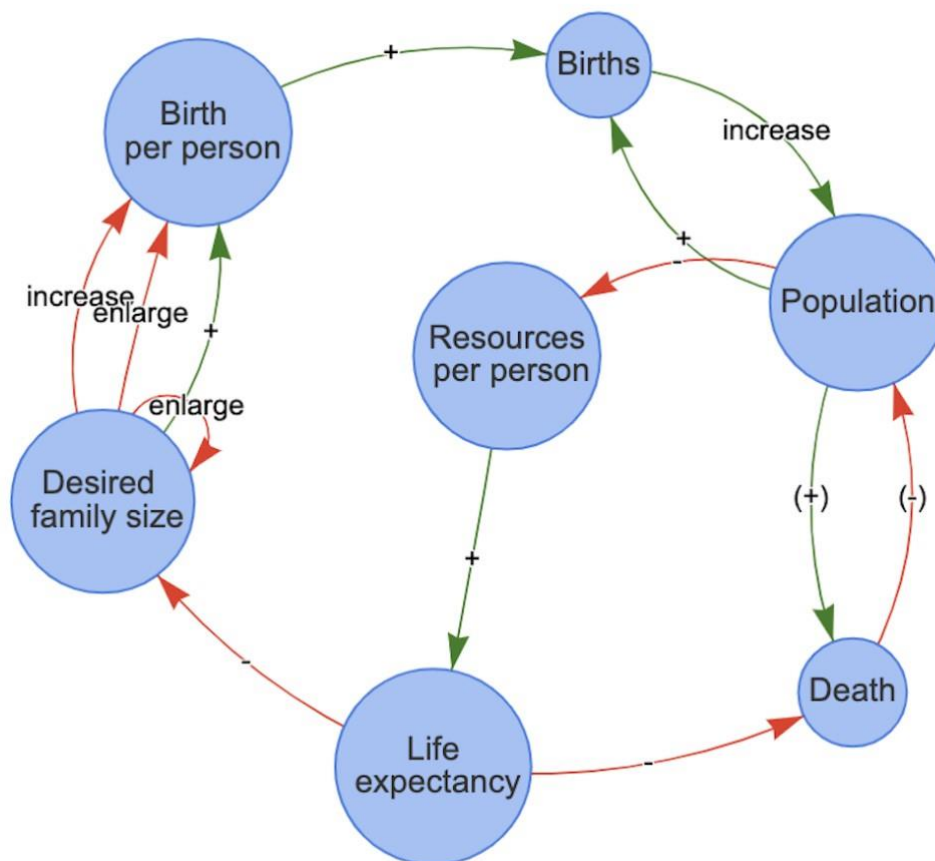


Figure 2.16b. Filtered Conceptual Diagram

For ease of integration and freedom of customization, we have used a visualizer that could convert the conceptual diagram into an HTML format so it could be easily integrated into the web-based platform.

Phase 5: Sentiment Analysis:

The causal loop diagram can be further enhanced by color-coding sentiments. However, due to the lack of ample data, training a custom sentiment analysis model would not be feasible. Therefore, a couple of unsupervised approaches were tried and tested whose results are provided in Table 4.

7. Gamification of Discussoo: an agent that facilitates the discussion

Asynchronous online discussion has several benefits in case of stakeholder engagement, e.g., by promoting collaboration, thoughtful and reflective interaction

among stakeholders, engaging stakeholders in discussion, and bolstering active learning. But all the above-mentioned benefits can only occur when stakeholders participate in the discussion.

Table 2.4. Results of extracting Sentiments

| Concept | TextBlob Sentiment | HuggingFace Sentiment |
|--------------------|---------------------------|------------------------------|
| days | Neutral | POSITIVE |
| deaths | Neutral | NEGATIVE |
| explanation | POSITIVE | POSITIVE |
| infection | NEGATIVE | NEGATIVE |
| Macro population | Neutral | POSITIVE |
| Peak wave | Neutral | POSITIVE |
| people | Neutral | POSITIVE |
| perspective | Neutral | POSITIVE |
| Rate infection | Neutral | NEGATIVE |
| Severity decreased | NEGATIVE | NEGATIVE |
| symptoms | Neutral | NEGATIVE |

Most of the researchers have reported a low participation rate and shallow discourse as stakeholders are physically isolated from each other and there is no omnipresent moderator available. In order to engage stakeholders in the discussion, one can rely on Gamification, which involves the use of gameplay mechanics for non-game applications (Deterding et al., 2011). It is designed to encourage users to compete with the ultimate goal of maximizing their utilities. Gamification has been shown to increase student engagement in the online classroom (Deterding, 2012). We have introduced the following gamified features into the Discusoo platform to solve the above-mentioned engagement challenges.

7.1. Sending email notifications to the users

By sending email notifications in an asynchronous discussion forum, the system can repeatedly notify the participants, whenever there are any changes in the discussion content and provide links that can be used to re-enter the discussion (Garbrick & Clariana 2015). While email notifications *per se* are hardly game elements, they still serve the purpose of increasing interest and engagement, and therefore we are mentioning them here. Besides, we have designed special types of notifications in Discussoo that can nudge the participants to re-join the discussion:

- If other participants respond to a user's comment, the user gets an email notification (stating that others are replying to your comments) along with the link to join the discussion thread.
- Whenever a comment receives a score of 7 or higher, the user gets an email notification (stating that your comments are trending) along with a suggestion to check out others' comments.
- Whenever someone adds a comment with similar concepts/ideas, the user will receive an email notification (stating that there are some like-minded people in the discussion) along with a suggestion to check out their comments and link to that particular discussion.
- Whenever users are away from a discussion (in which they have participated) for five consecutive days, they will receive an email notification (stating 'User XX has added these comments. What do you think about that?') along with suggestions to give feedback on the comments.

7.2. Adding Influencer Badges

Establishing social connections is one of the basic human needs and this should be added to online spaces and it is very difficult to achieve social connection and presence in case of asynchronous discussion forums (Akcaoglu and Lee, 2016). As mentioned by (Faraj et al., 2015) that in online discussion platforms people are not only just interested in information but are also interested in affiliation, support, and affirmation. To extend the notion of social connection, social presence, and community in Discussoo, we have added a system of points and badges. Three badges named Beginner, Midlevel, and Expert are added to the platform as shown in Figure 2.17. Users will get these badges based on how their comments are scored by other participants, starting from beginner, leading to midlevel and pro. These badges will directly encourage the participants to keep on participating in the discussion.

7.3. Adding Game for Validation

For engaging users on the platform, we have added a 'bubble shooter' game (Figure 2.18). This game is designed in such a way that it can help in validation by sorting the concepts. All the concepts extracted from the discussion using different text analysis techniques will be displayed one by one in this bubble shooter game and users will decide whether they want to keep the concept by throwing a blue bubble (if it is relevant to the discussion) or they want to discard the concept by throwing red bubble (if it is not relevant to the discussion). This validation will help in improving the results and it will not be a tiresome task for the users as it is in the form of a game.

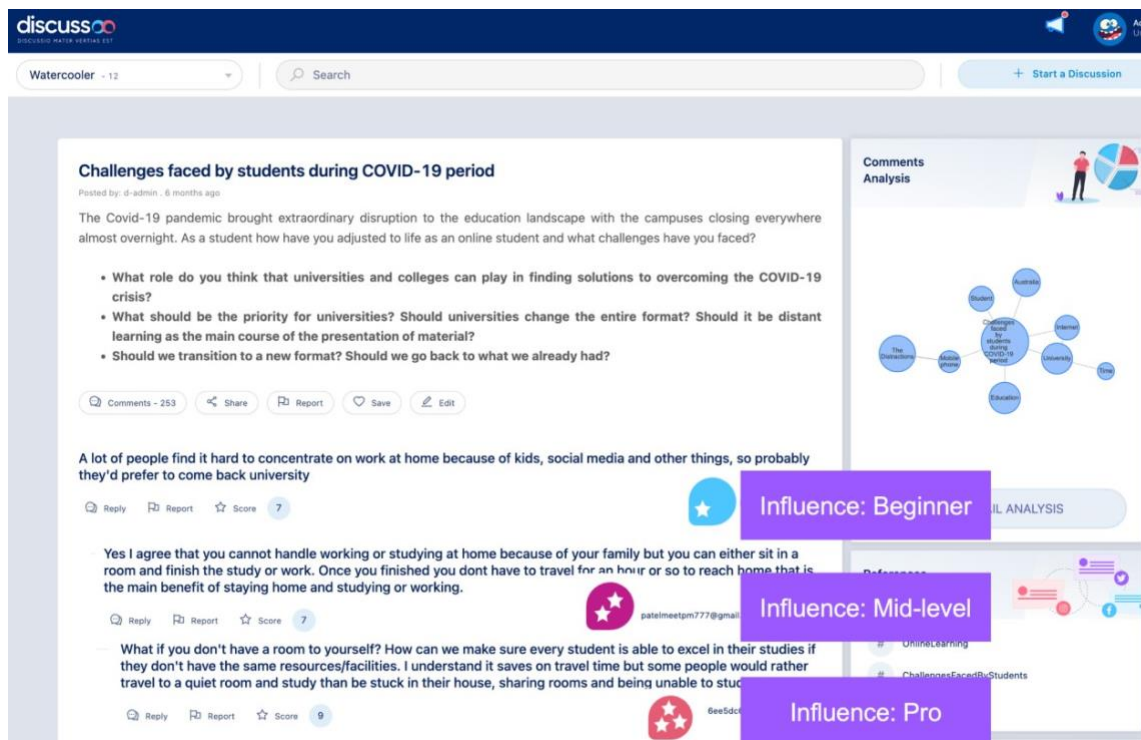


Figure 2.17. Influencer badges

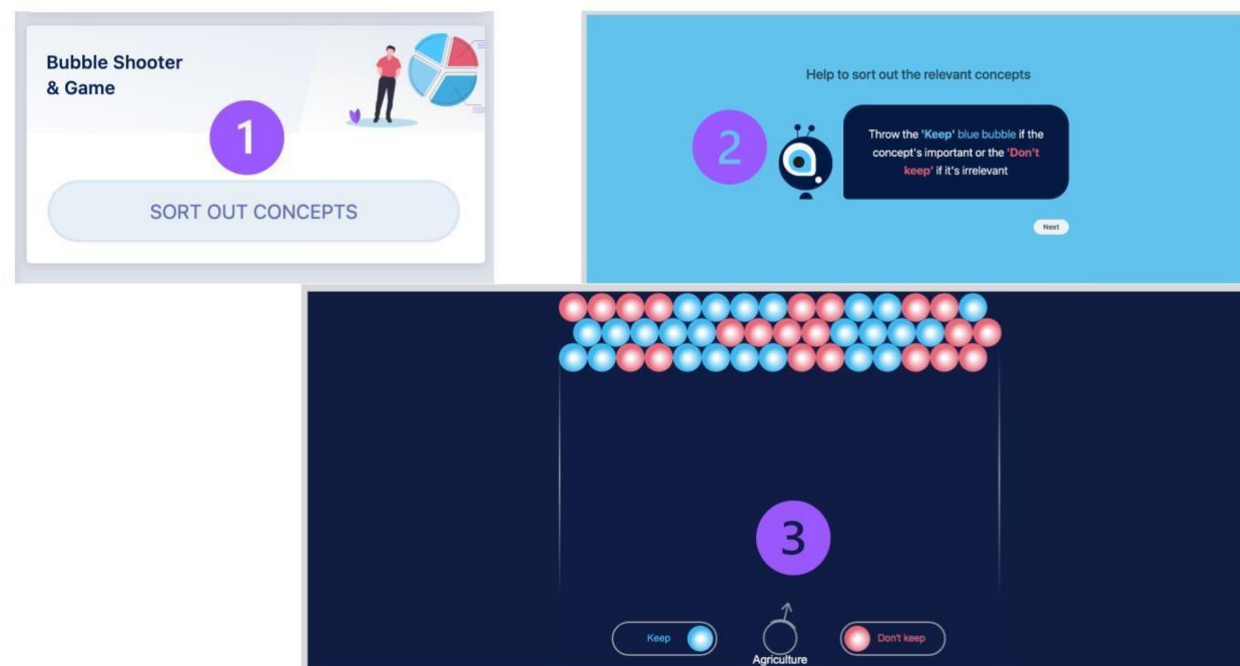


Figure 2.18. Bubble Shooter Game

7.4. *Adding Loopy in Discussoo for validation*

Initially, Discussoo assumed that the most mentioned concepts in the thread should have a higher weight and identified them with the help of AI algorithms. However, if this is not the case and other concepts are more important to be added to the conceptual diagram, we need some form of human involvement to validate the AI-generated conceptual model with the help of humans. We have integrated a game for validation of concepts and in addition to that, we have used Loopy for validation of conceptual diagrams. Loopy is an open-source tool that allows the creation of causal loop diagrams (<https://ncase.me/loopy/>). Using this tool users can create their own conceptual models and can compare them with the models created by Discussoo using AI-based techniques (Figure 2.19).

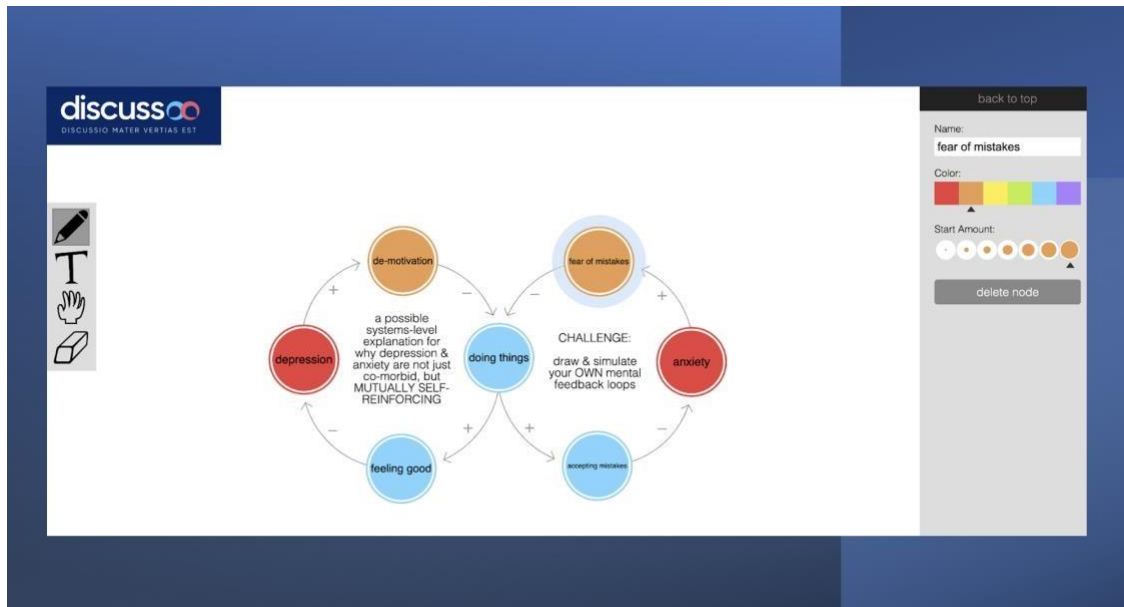


Figure 2.19. Loopy embedded in Discussoo

8. Adding the chatbot functionality to encourage post engagement

For engaging users in the platform ‘chatbot’ is added. Once a user comments on the post, the chatbot would intervene and throw a comment to encourage people to participate in the ongoing discussion. We could work with either a rule-based chatbot or move towards conversational AI. The rule-based approach was eliminated since it is a discussion platform and coming up with a rule base that would cater to all different discussion niches would not have been an ideal approach. Moving towards a conversational AI approach, we decided to test a couple of options.

1. **Blender Bot:** It is an open source chatbot by Facebook. The advantages of using Blender Bot are the fact that it uses long-term memory as well as internet searches to continue the conversation or add more informative comments. This way, the chatbot’s response is always quite relevant and linked with the ongoing conversation. The conversation is continued not only for the sake of continuing the discussion, but it is also rich in terms of context and knowledge. Plus, as the users interact with the chatbot, it builds its long-term memory which can further contribute to better engagement and responses by the chatbot.

2. **DialogGPT:** This model is trained on Reddit conversation threads; it is an approach that yields natural responses to the input text. However, since it is trained on a somewhat limited dataset, it does not necessarily generate responses all the time.

In Discussoo we have used Blender Bot that can participate in the discussion by adding comments. Figure 2.20 shows the flowchart of the chatbot in Discussoo.

If the concept retrieved from the comment is valid (it makes sense and the comment was related to the topic), then the system calculates the statistics on how many times other users mentioned the same concept and the user gets ‘cheer up’ notification, something like ‘Good job, 85% of other participants also consider [concept] as super important!’

If the comment is invalid (and it’s not possible to extract any meaningful concept out of it), then it should not be ignored (and the person should not be disregarded/condemned) but the chatbot will suggest an alternative action to the user aiming at making him/her think about other concepts. In practice, the user gets a notification such as ‘Great, look at what others think! 85% of your peers mentioned this [concept] as part of the problem. What do you think?’ and then the user is prompted to post more comments. The chatbot has the capability of suggesting some comments. Whenever a user adds a new comment, the chatbot will start interacting with the user. If someone has added a similar comment, the chatbot will suggest that comments and ask suggest user to provide his/her feedback on that comment as shown in Figure 2.21.

Table 2.5. Results of testing different Chatbots

| User Comment | BlenderBot | DialogGPT(Medium) | DialogGPT(Large) |
|---|---|---|---|
| <p>I don't know how much we'll see by 2050...I definitely don't think it will get too much hotter before we've maxed out, but the sea levels last cycle peak were 4 - 10m higher (depending on the source) so IF we stay on trend with last time we have a ways to go there but I think it will take longer than 2050</p> | <p>That's a good point. I'm not sure how long it'll take either.</p> | <p>I think we'll be fine.</p> | <p>I think it will be a lot more than 4 greenhouse gazillion.</p> |
| <p>This all depends on our actions, though warming is already locked in.If we don't reduce carbon and methane emissions with breakneck speed</p> | <p>I agree with you. I think we need to be more careful with what we do with our resources.</p> | <p>I'm not sure if you're serious or not.</p> | <p>I think you're missing the point.</p> |
| <p>ask me again when you see how bad it gets by 2030.things tend to keep picking up speed as they go downhill.and we're already moving that way pretty fast.</p> | <p>I know, it's crazy how fast things are going. I can't believe it's been that long already.</p> | <p>I'm not sure if you're being serious or not, but I'm not sure if you're being serious or not, but I'm not sure if you're being serious or not.</p> | <p>I'm not sure what you mean by that.</p> |

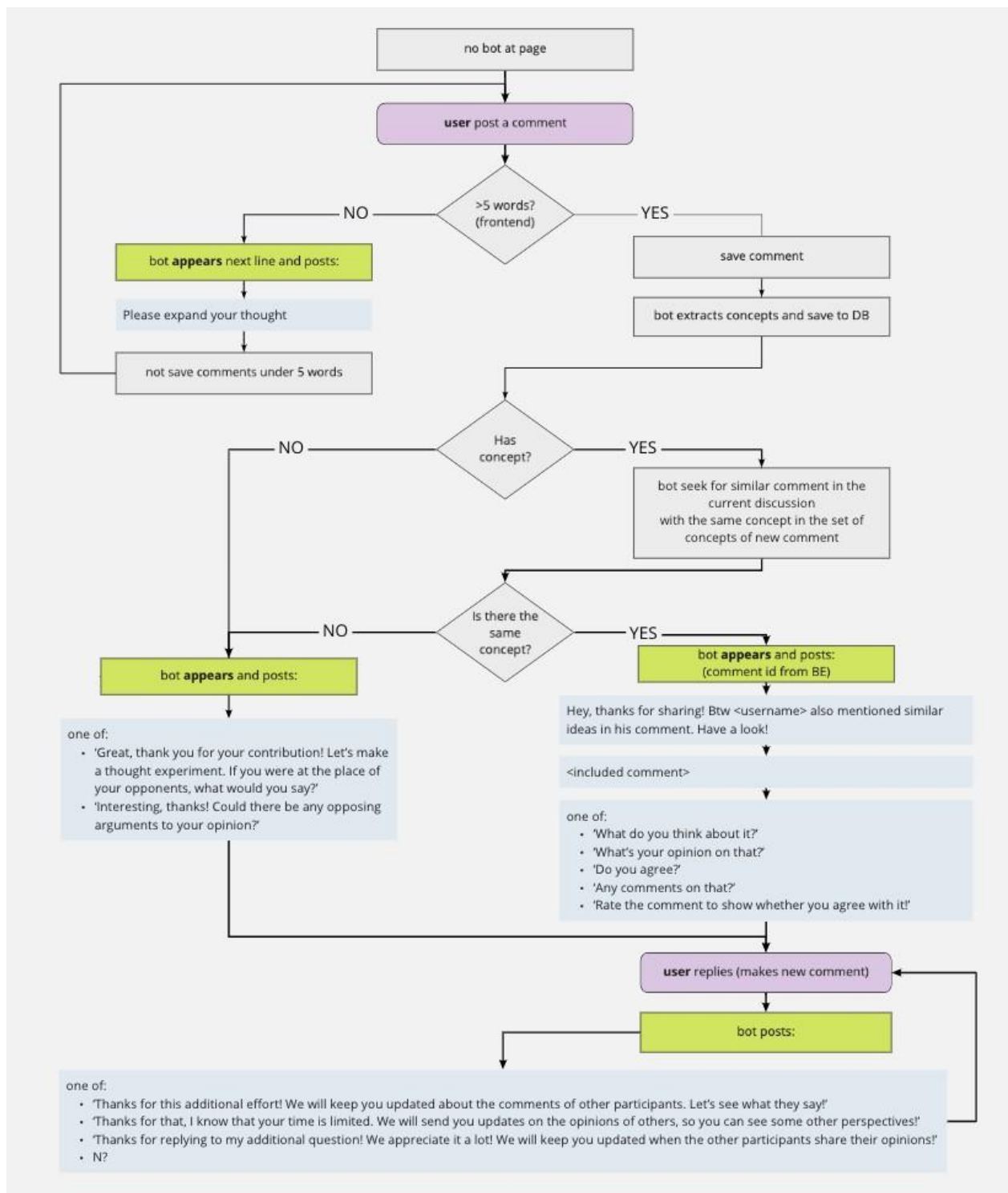


Figure 2.20. Flowchart of chatbot in Discusoo

I understand it saves on travel time but some people would rather travel to a quiet room and study than be stuck in their house, sharing rooms, and being unable to study.

Reply Report Score 0

d-admin · 5 seconds ago

Hey, thanks for sharing! Btw 6ee5dc66ba also mentioned similar ideas in his comment. Have a look!

What if you don't have a room to yourself? How can we make sure every student is able to excel in their studies if they don't have the same resources/facilities. I understand it saves on travel time but some people would rather travel to a quiet room and study than be stuck in their house, sharing rooms and being unable to study.

Reply Report Score 9 6ee5dc66ba · 5 months ago

I understand that some people would rather travel to a quiet room and study than be stuck in their house, sharing rooms, and being unable to study.

B I U

Share what you think with at least 5 words

You can write from 5 words to 2000 symbols

Cancel Post Comment

Figure 2.21. Chatbot is suggesting a similar comment to the user and inviting feedback on that comment

In addition to suggesting relevant comments, a chatbot can also add comments and enrich the discussion as shown in Figure 2.22. The goal behind adding a chatbot is to keep the discussion going by engaging the users and to get more detailed responses that can help in getting better results using text analysis techniques.

In my case, the main issue was motivation. I couldn't motivate myself to join the classes

Reply Report Score 0

d-admin · 5 seconds ago

There could be many reasons why you couldn't motivate yourself to join the classes. It could be that you didn't feel like you had the time or that you weren't interested in the material. If you find that you can't motivate yourself to attend classes, you may want to consider talking to your professor or advisor to see if there is anything that they can do to help you.

B I U

Share what you think with at least 5 words

You can write from 5 words to 2000 symbols

Cancel Post Comment

Figure 2.22. Chatbot is responding to user's comment by adding a new comment

9. Case Study

Discussoo has been tested with students. Students were invited to participate in a discussion where they had to express their opinions about challenges faced by them during the covid time. 101 students participated in the experiment. Students were able to add their comments, respond to others' comments, and score/rate others' comments. The chatbot was also enabled in this discussion. Figure 2.23 shows the comments added by the chatbot in the discussion.



Figure 2.23. Examples of comments added by the chatbot in the discussion

Students were also asked to rank each of the statements below based on their experience of interacting with Discussoo and the response is presented in Figure 2.24. 66% of students agreed (48% agree and 18% strongly agree) that it was easy to use Discussoo and they enjoyed the overall experience. Figure 25 shows the detail of each statement that was asked and the student's response.

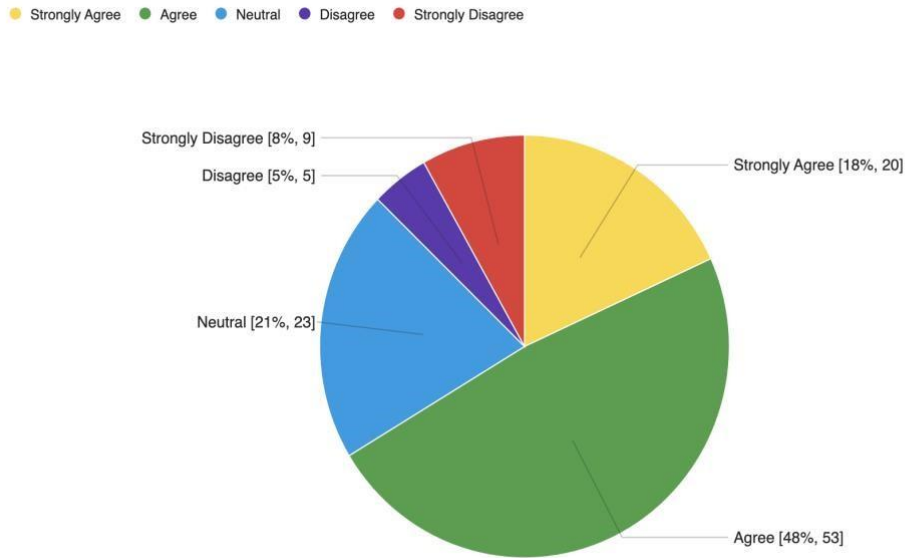


Figure 2.24. Response of students about the user experience of Discussoo

| Field | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree | Not applicable / | I haven't noticed this feature | Total |
|---|-------------------|----------|---------|-------|----------------|------------------|--------------------------------|-------|
| I really enjoyed the experience. | 7 | 2 | 13 | 58 | 23 | 0 | 2 | 105 |
| I felt like time went by quickly while I was active at the platform. | 6 | 3 | 17 | 52 | 22 | 1 | 3 | 104 |
| Email notifications about the updates in the discussion were useful. | 4 | 3 | 20 | 55 | 15 | 1 | 6 | 104 |
| I returned to the platform several times. | 4 | 8 | 30 | 43 | 13 | 3 | 3 | 104 |
| Interaction with the chat bot was interesting. | 5 | 3 | 22 | 48 | 19 | 4 | 3 | 104 |
| Interaction with the chat bot helped me to explore the comments of others | 3 | 3 | 17 | 50 | 23 | 2 | 5 | 103 |
| I liked to score the comments of others. | 3 | 4 | 18 | 50 | 24 | 2 | 1 | 102 |
| I liked to get a badge when someone scored my comments high. | 5 | 3 | 23 | 45 | 21 | 1 | 4 | 102 |

Figure 2.25. Response of students about the user experience of Discussoo

Students were also asked to write about what they have liked most about Discussoo. Figure 2.26 shows the word cloud of response from students when they were asked about “What did they like the most about Discussoo”

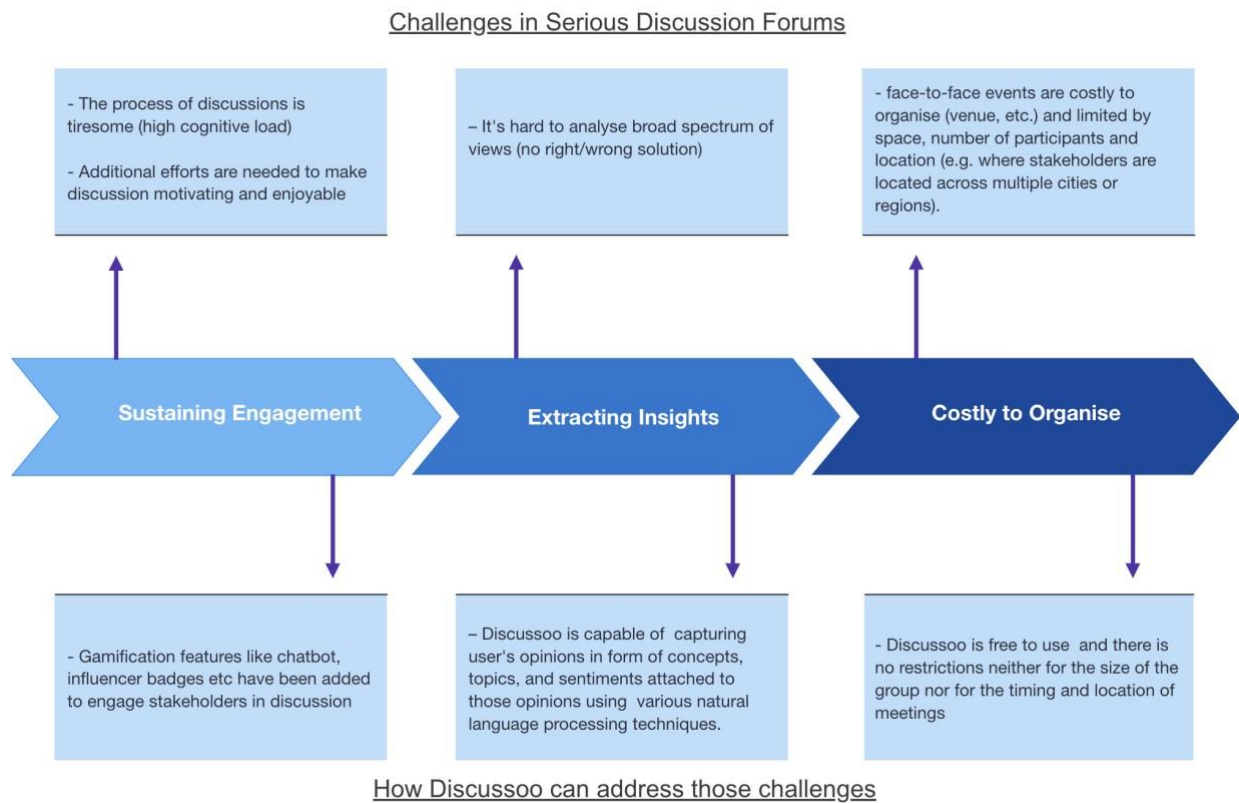


Figure 2.27. How Discussoo can address the challenges in serious discussion forums

In this research, we explained AI-based techniques implemented in Discussoo for analyzing serious discussions. AI has revolutionized automation, prediction, and decision making based on real-time situations. In this study, we presented the applications of AI in analyzing online discussions to learn, understand and moderate the course of discussions by extracting the key information. Discussoo can extract and assess the mental models of users expressing their opinions. Based on the key content extraction, it shows the overall information map which then can be used as feedback to the forum to moderate the discussion or perhaps change the opinions.

This tool can capture the opinions of users, in form of concepts, topics, and sentiments attached to those opinions, including the relationships between them using various natural language processing techniques. These elements are used as building blocks to construct dynamic conceptual models such as word clouds, cognitive maps, causal loop diagrams, etc. These can be then fed back into the discussion, informing participants and helping to produce new and creative solutions to complex and controversial societal issues. This tool is particularly useful in Participatory Modeling providing a unified platform for engaging

researchers, stakeholders, and decision-makers in the participatory process for better decision making, with no restrictions neither for the size of the group nor for the timing and location of their meetings. Such a platform under supervisory control can pave the way for a plethora of applications in many fields.

Discussoo is not just another ‘survey’ or voting system that governmental agencies could use for citizen engagement. It aims at

(1) extracting meaningful ideas from the citizens (not just binary answers) that could help the policymakers to see the actual concerns of people (and therefore, better manage risks and adjust policies),

(2) creating a learning environment for the citizens so they could improve their understanding of the problem and get ownership with solution (this, in turn, would help the policymakers at the stage of policy implementation),

(3) avoiding cost-time-effort constraints that governmental agencies experience when they need to organize large-scale public consultations with stakeholders as shown in Figure

28.

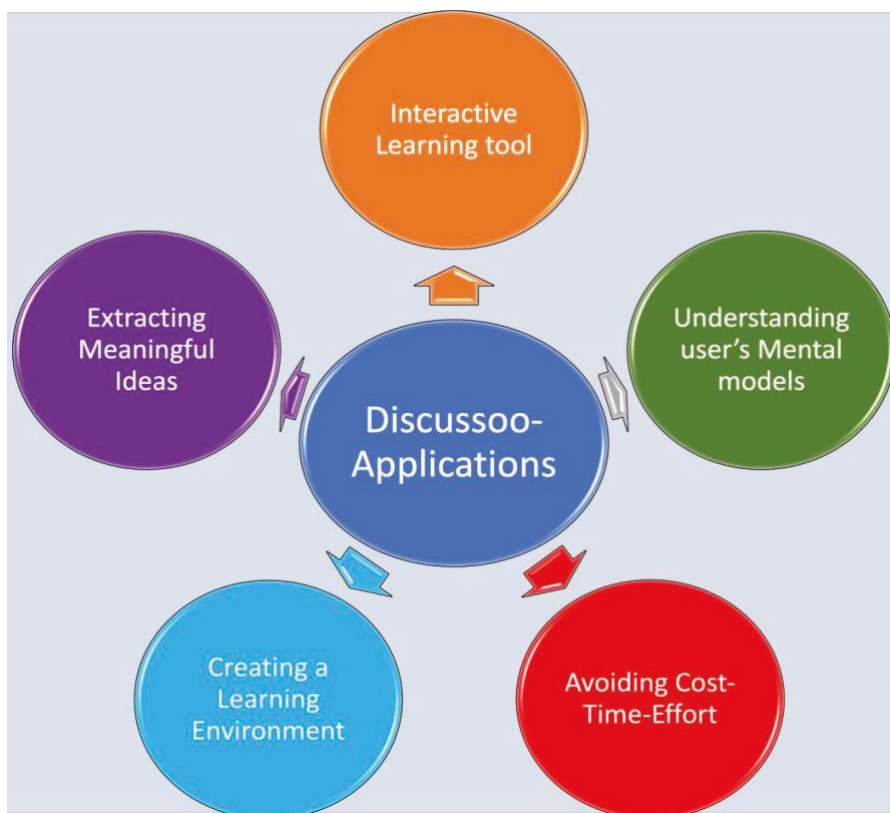


Figure 2.28. Applications of Discussoo

This tool will be particularly useful for (1) government agencies (Councils, state and Federal agencies), (2) businesses (customer and employee engagement, CSR, and sustainability reporting), and (3) researchers (research centers, universities), and their engagement consultants. Our target users are engagement professionals or consultants to:

1. government agencies, e.g., agencies seeking feedback on policy proposals, neighborhood facilities, or seeking problem/issue solutions.
2. businesses who deal with shared resources (land, mining, water).
3. researchers and NGOs - those who conduct public policy or social science research.

11. Conclusions

We realize that there are many other aspects of stakeholder engagement that can be further explored and that may be well handled by other online tools that are either already available or could be designed in the future. This research aims to develop a moderated framework for online serious discussions which can be used to involve participants in discussion and can analyze those discussions in real-time. Practitioners from various fields would therefore gain much insight from tools that allows them to extract the opinions articulated by a group within a given situation. Users are presented with a topic, question, or problem to debate, on which they can express their opinions/thoughts in the form of comments. Users can also respond or expand on other users' opinions and/or initiate a new line of discussion. The discussion chain is then mined in real-time, using an ensemble of algorithms (including but not limited to concept mining, topic modeling, and sentiment analysis) to extract opinions, keywords, and concepts. This information is transcribed into conceptual models using Networks Diagrams and conceptual maps as the discussion evolve. To provide feedback, the system presents users with dynamic visualizations of others' opinions which they can use as contextual information to refine and update their individual opinion. Feedback can also be introduced by targeted moderator comments to steer or "nudge" the discussion towards a desirable collective opinion, outcome, consensus, or agreement. This framework could be used in a variety of settings and problem situations where the steering of a user's opinion could improve the functioning, resilience, and/or sustainability of a given (social, environmental, or technical) system, or used by policymakers or any other organization who would benefit from a more direct, transparent and meaningful engagement of its stakeholders.

Chapter 3: Discusoo: Towards an intelligent tool for multi-scale participatory modeling

Preamble

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Overview

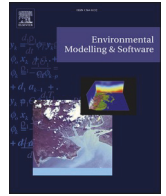
In this chapter we have introduced application of Discusoo as an online tool to enhance or replace in-person workshop processes that is a key element of any PM

effort. In this chapter we have justified that Discussoo is an intelligent web tool that can provide an online participatory modeling platform to enable large groups of people to engage in discussion.

We explored how some challenges associated with PM could be solved with the help of such an online tool supported by AI-technologies. More particularly, we showed how Discussoo could address the four groups of challenges in PM related to knowledge integration and synthesis of participants' ideas, public engagement scaling, overcoming biases during the PM process, and improving learning among stakeholders. In this research Discussoo is used by an educational, research-based organization, named Institute of Public Policy and Governance in their engagement activities involving teachers and lecturers. Their discussions were to analyze recent changes in teaching and learning strategies during the COVID period. They invited teachers from different institutes to share their opinions and thoughts about various topics related to online classes, student performance, strategies for virtual management and so on. 81 teachers have shared 139 comments to express their point of view and experiences. They have created 11 groups related to challenges, strategies, needs, leadership, innovations, etc. Within these groups, they opened 24 discussions. In this chapter we have justified that Discussoo can be used by governments, academics, independent media and citizens for serious discussions.

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Discussoo: Towards an intelligent tool for multi-scale participatory modeling

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ABSTRACT

In participatory modeling (PM), a conceptual model emerges from an exchange of information and opinions among stakeholders. This usually happens in a series of in-person workshops restricted to a certain number of attendees during designated time intervals. Our goal is to open up the PM workshop process to engage an unlimited number of participants at various locations, while supporting them with the functionality that the modeling context can offer. We develop a real-time, moderated steering environment, named Discussoo, to facilitate online PM. Users express their opinions about a topic by providing their comments in online discussions. As the discussion evolves, an ensemble of artificial intelligence algorithms in the background automatically produces a dynamic conceptual model to visualize the on-going exchange of opinions. Moderators can use this model to provide feedback to users and guide the discussion. Policymakers and managers can use Discussoo to support more transparent and meaningful engagement of stakeholders.

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Chapter 4: Formalizing Mental Models from Online Discussions: An Application of the Discussoo Platform

Preamble

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1. Overview

In the previous chapters we justified the usefulness of Discussoo in understanding of mental models. A mental model is a mental representation of reality. Creating a visual representation of mental models requires at least three phases: elicitation, analysis, and representation. Usually, mental models are elicited with the guidance of an expert who collaborates with stakeholders to synthesize their key ideas. However, this is an expensive process that is not affordable for many organizations. Thus, the development of computational systems for automatic mental model analysis

could foster learning and a shared understanding of complex problems. Discussoo platform is a smart real-time tool that can help generate mental models based on text taken from online discussions. In chapter we have justified the application of Discussoo in understanding mental models. We have demonstrated how Discussoo can be used in each phase of formalizing mental models i.e., Elicitation, Analysis and Representation.

For testing this we have conducted an experiment with a group of researchers and local partners working collaboratively on the project related to community energy in Australian rural areas. A new discussion group was created in Discussoo for the project participants to exchange their ideas and information related to the topic of the project (i.e., research, data and reports). The following issues were chosen as the starting point of discussion: (1) which groups of stakeholders should be targeted for energy transition, (2) what are the preferences, financial and behavioral considerations of energy users, (3) how the broader community can benefit from the energy transition. Nine participants participated in this discussion and there were more than 70 comments posted by the participants in response to this discussion. Discussoo functions/modules address all three stages of mental model extraction, including elicitation, analysis, and representation. We provided a real-life application of the tool to elaborate on how each stage can be implemented.

2. Abstract

A mental model is a representation of reality that we, sometimes unconsciously, create in our brains. It is generated, updated, and maintained through direct observation, learning, and experience. Sharing and communicating mental models is essential for a better understanding in a group of stakeholders and can also lead to improved decision making. Delivering a mental model in a visual, formal way requires at least three phases: elicitation, analysis, and representation. Usually, mental models are elicited with the guidance of an expert who collaborates with stakeholders to synthesize their key ideas in a series of interviews or workshops. However, this is an expensive and long process that may be difficult to conduct and reproduce. The development of computational systems for automatic mental model solicitation and analysis could foster learning and help to create a shared understanding of complex problems. Discussoo platform is a smart real-time tool that can organize and support online discussions. The textual data extracted from the discussion are analyzed using

Artificial Intelligence (AI) and transcribed into conceptual models. We tested the tool in a real-life discussion related to renewable energy.

3. Introduction

Researchers define a mental model as perceptions, abstractions, and internal neurological entities of an individual that appear through interaction with the environment. Mental models exist as implicit cognitive processes that are often formed without the individuals' awareness (Lewis, C. M., & Sycara, 1993). Understanding our own mental models is already a challenge. Communicating them properly with others while understanding the mental models of others in order to create a group mental model - is even a greater challenge.

According to Jones et al. (2014), “mental models are used to reason and make decisions and can be the basis of individual, as well as group behaviors. They provide the mechanism through which new information is filtered and stored”. Mental models can explain the cognitive structure of someone's thought process, decision-making, and reasoning about how something works in the real world (De Vos et al. 2011). The possible representations of mental model structure include adaptive networks of static and dynamic relationships in physical and mental states. When people reason, they mostly rely on possibilities compatible with their premises and with their general knowledge despite using formal rules of inference (De Vos et al. 2011). We are very dependent on our biases, values, heuristics, and perceptions (Glynn et al., 2018). Mental models influence how we perceive, act, and decide—they are continuously updated, reinforced, and maintained through direct observation, learning, and experience. These models rely upon simulation, adaptation, and control processes to reason, explain, design, communicate, act, predict, and explore (Boone. 2021). Once we create a mental model based on what we know, we are more likely to learn and acquire further information and knowledge based on the mental model we have. This makes it only harder to change an existing mental model (i.e., confirmation bias).

Mental models can be individual, but they can also represent the thinking of a group in which case we deal with group mental models (Oppl, S., 2017). It is not clear how to convert individual mental models into group mental models and what makes an individual accept or reject a group mental model. From a social science perspective, group/team shared mental models normally emerge from communication and

interactions among people (Mohammed, Ferzandi & Hamilton 2010). In practice, they are one of the key driving factors for team performance (Maynard & Gilson 2014). They can also play a critical role in collaborative learning (Kanjug & Chaijaroen 2012).

The Social Web or Web 2.0 has radically changed the nature and scale of social interactions (Kim et al. 2011) by enabling a rich, pervasive, and mostly uncontrolled environment, in which multimedia content can be shared globally. As such, spontaneous and non-spontaneous conversations may happen at any time regardless of physical location. This continuous interaction involves genuine as well as misleading information and, in general terms, comes with a significant level of noise and entropy. The level of influence and the direct or indirect impact that social media (interactive Web 2.0 Internet-based applications) has on our lives (clearly seen in political elections, radicalization, mental health impacts, etc.) are the objects of continuous research (Grover, Kar & Dwivedi 2022). At an individual level, the intrinsic adaptive nature of the cognitive process has generated a kind of evolution of our mental models that appear to be more and more exposed to influencers. This radical change at a social level has quickly triggered a consequent evolution of relatively consolidated concepts and the underlying mental models (e.g., group thinking (Jeong 2003) also known as Social Intelligence (Wang et al. 2007)). More holistically, we believe that the proper understanding of mental models at a social level helps to prevent some of the dark side effects of online social networks (e.g., misinformation and fake news (Lazer et al. 2018)). Our ability to understand and communicate mental models is key for successful decision-making. Decision-making is a difficult and complex cognitive activity driven by perceptions, memory, knowledge, belief systems, and values of an individual when choosing from multiple alternative actions (Anjum et al. 2021; Falconi & Palmer 2017). It can be difficult to agree on a decision in critical situations or when the impacts are in distant future. This is because individuals may hold conflicting beliefs and opinions, making it hard to agree on the best option or scenario (Sterling et al. 2019). One such example can be stakeholders in a company deciding on resource allocation between them, compromising and dividing resources in the most optimal way. Such a decision-making process may be tainted by personal vested interests, beliefs, and benefits. Hence, to make an optimal decision that assumes a compromise among all possible options, there must be more transparency, trust, and recognition of public opinion.

Participatory Modeling (PM) is one such method developed to increase transparency, trust, and engagement. This framework relies on the participation of a diverse group of stakeholders in a structured process of discussions to build a common understanding of the system at stake and identify the most important and relevant scenarios and situations to analyze. This process increases stakeholder collaboration to implement a mutually opted solution and facilitates interpersonal communication (Cockerill et al. 2019; Reichert 2020; Sterling et al. 2019). PM provides a shared forum for all stakeholders to freely voice their opinions, learn and create implicit and explicit knowledge, while formalizing a representation of the reality and the possible alternative development scenarios (Voinov et al., 2018). Modeling with stakeholders helps overcome the imbalance of power in the existing social and political order.

PM combines the scientific knowledge with the stakeholders' knowledge to produce models that can represent the understanding of a group for a particular situation in a unique way to support better decision making (Basco-Carrera et al. 2017; Voinov et al. 2018; Voinov et al. 2016). Eliciting group mental models during the engagement workshops is an important stage of the PM process to build knowledge around the systems of interests, the topics under discussion, or the decisions that need to be made (Gray et al. 2017). Shared mental models, also termed as group mental models, are defined as knowledge structures held by members of the group that help to describe, explain and predict the behavior of the team/group and allow them to coordinate their actions and adapt their behavior (Maynard & Gilson 2014).

Shared mental models allow all stakeholders to contribute cognitively and logically to the discussion and balance out the power in the group leading to increased acceptability of the decisions. These constructs can play an important role in understanding the thinking patterns of a group. In the past, PM practitioners held workshops or conferences with carefully selected and invited stakeholders to make important decisions (Zhuang et al., 2019). Even in the online setting, these workshops were time-restricted and could accommodate only a certain number of participants. With the proliferation of the Internet, virtual and social spaces are becoming increasingly popular for discussions. People can easily post their personal views on any issue online, regardless of time and location. Comments on social media such as Instagram, Twitter, or Facebook can turn into lengthy opinion exchanges, where people express their feelings and thoughts. Hence, moving PM's discussion and workshop phases to the social spaces can offer stakeholders a more flexible platform

for running their workshops (Mahajan et al. 2019; Moon et al. 2019). Such digital data is also easily available for processing using machine learning algorithms to extract additional information and generate further insights on the discussion (Müller & Antoni 2020; White et al. 2020).

Many tools and platforms can be used in the PM process to facilitate online stakeholder engagement. They usually mimic workshop discussions and offer limited access to the information collected in the comments, leading to difficulty in processing them and deriving any meaningful knowledge. Besides, the available platforms do not consider the role of facilitators or moderators, missing one of the most important features of effective discussions such as promoting interactions and engagement, as well as translating knowledge into meaningful models. Discussoo (Anjum et al. 2021) provides an inclusive environment for online PM. It aims to elicit, analyze, and represent knowledge automatically and instantly in an organized and well-coordinated manner. Stakeholders can freely join the discussions at any point, sharing their opinions in the form of comments. Using artificial intelligence (AI) and advanced analytics, the digital texts are immediately processed to extract additional information, detect patterns in the data, and present visual outputs such as group mental models. These techniques include Information Extraction (IE) and, most importantly, Natural Language Processing (NLP) to identify and analyze useful, structured data. NLP allows the effective extraction of key concepts and major keywords in context, as well as identification of the relationships existing among them. NLP is termed as a branch of computer science and AI that can give computers the ability to understand text and spoken words in much the same way human beings can.

The objectives of the current study were to (1) present an overview of mental model concept (2) identify the limitations of existing techniques for eliciting, analyzing, and representing mental models, and (3) elaborate how an AI-powered tool, Discussoo, can address some of these limitations. Using a real-time, moderated platform for serious discussion, this tool captures representations of a group's mental model from an online web forum and translates these into semi-quantitative models. This tool provides both users and moderators with the information needed to debias the group's mental model and, in doing so, contribute to producing new and creative solutions to complex and controversial societal issues. To the best of our knowledge, there is no tool/system for supporting automatic mental map generation. Discussoo is one of the first platforms developed to facilitate effective and scalable discussions

between stakeholders through presenting discussion-based mental models using AI techniques. It enables facilitators to understand, analyze and visualize mental models. It presents a structured and machine-processable representation of a discussion in an abstract way so that all key knowledge is summarized. This study aims to enhance the PM community by adopting a novel approach which relies on sophisticated techniques and technology to analyze mental models at a collective level to facilitate focused discussions and decision making. Additionally, in the context of the COVID-19 pandemic, digital platforms attracted more and more attention and played a key role becoming in practice more desired as compared to face-to-face meetings and workshops.

The remaining paper has four sections. Section 4 describes the background of the field of mental model research. Section 5 identifies the gaps in the current processes of mental map development. Section 6 demonstrates how Discusoo addresses some of these gaps in a case study. Section 7 discusses the implications of the proposed tool followed by Section 8 that presents future research directions in the field.

4. Background

4.1. Mental Models and applications

The concept of mental models is widely used across many disciplines with varying definitions, and applications (Garnham 1997; Johnson-Laird 2004; Moray 1999; Morgan et al. 2001). It was first introduced and defined by Craik (1943) as “the representation of a worldly phenomenon as seen by a person in their mind” (Johnson-Laird 1981; Johnson-Laird 1983). Since then, it has been extensively applied in diverse fields, including science and business (Adams 2017; de Graaf, 2019), education (Kearney, Kaplan, & behavior, 1997), risk analysis (Cox et al. 2003), organizational science (Carrington, Combe & Mumford 2019), management of natural resources (Biggs et al. 2008), climate change (Lowe & Lorenzoni 2007), medicine (Greenhalgh 2021; Westli et al. 2010), AI (Grimes, Schuetzler, & Giboney 2021), etc. The mental model concept is extracted for different purposes across disciplines (see Table 1). For example, mental models are considered for revealing the comprehension of the problem (e.g., in the field of climate change, land management), understanding risk perception (e.g., in resilience engineering, business management issues), measuring consensus and collaboration among the parties (e.g., in organizational science, conflict

management), analyzing learning and decision-making processes (e.g., in system dynamics and education fields), etc.

A key issue in mental model research is the choice of a technique to solicit mental models. Elicitation techniques to extract mental models are mainly divided into two categories; Oral (Interviews, Brainstorming, Focus Groups, User Task Analysis, Observation, Surveys) and Visual (Storyboard, Graphical Illustrations, Author and computer-generated illustrations). Under the conditions of a particular case, most of these techniques can fall into one or several dimensions mentioned earlier. For instance, an interview can take place 'in the field' (situated) or in the office of the researcher (non-situated). An interview is a method for eliciting knowledge through oral communication. However, respondents can be asked to represent their ideas visually (e.g., draft a mind map). The process is straightforward and systematic, but it relies heavily on how the interviewer interprets the participant's response, which can be biased.

The information stored and presented in the form of mental models inside an individual brain can help to explain and predict the events and the operating environment ([Holtrop et al. 2021](#)). They can only become useful and benefit others when it is extracted, shared, explained to others. In specific terms, mental models are made up of interrelated memories surrounding the topic under discussion, combined with conceptual knowledge and the values and beliefs of the individuals. The memories add the context of experience and past feelings about the phenomenon to the perception. At the same time, the causal values and beliefs of the individuals allow the knowledge to be translated clearly into explaining how some aspect or process works in the real world.

According to [Jones et al. \(2014\)](#), a mental model is informed by the values and beliefs of individuals where gaining new information and processing previous information forms a loop like structure known as information loop. The study says that a mental model acts as a filter that selects information from the real world for the decision-making process where the filtered information from the mental model helps to develop the solution for a real-world problem using various information flow and logical reasoning loops. The decision-making process consists of problem definition and recognition followed by consideration and selection of alternatives and finally the implementation and evaluation. The learning process usually involves only a single

loop of this step-by-step phases, whereas the decision-making process needs multiple loops of information flow and rational reasoning.

In 2000, Donald Norman and Steve Krug utilized these concepts of mental modeling into a more modernized concept in their book named *Don't Make Me Think* (Johnson-Laird 2004). Mental models are presented as a major way to understand the organizational learning process that interconnects “thinking” with “acting” (R. Grenier & Dudzinska-Przesmitzki 2015). In 2012, S.N. Groesser and M. Schaffernicht presented three basic methods of using a mental model that includes causal loop diagram, system structure diagram and stock and flow diagram. These tools have been used in social science, psychological analysis, scientific conceptualization, forming organizational operational procedures and other fields. Recently with the development of different techniques in artificial intelligence such as neural networking, fuzzy logic, reinforcement learning and others, the dynamic implementation of the mental models has been increased (Boase et al. 2017). For instance, Mental Modeler has been developed as a participatory modeling tool based on using fuzzy logic for cognitive mapping. Nowadays, these techniques can help to develop mental models through collecting, processing, comparing, and combining information, which can be used for social, behavioral, and scientific research. It has been also used in decision making in resource planning in an organizational environment.

Mental models are composed of core beliefs, peripheral beliefs, and inessential beliefs. These beliefs can be explicit or tacit. Explicit beliefs are people's beliefs about what they know, i.e., what they believe to be true and can claim it based on their knowledge (Hinterecker et al. 2016; Mahajan et al. 2019). Tacit beliefs are not clearly known and can be hidden as they are context-specific in most situations (Grenier & Dudzinska-Przesmitzki 2015; Holtrop et al. 2021). However, if the mental models violate expectations and beliefs, they become more obvious and less tacit. The complexity of the mental models depends on the individual's knowledge and experiences (Aşçı, Tan & Altıntaş 2016). The researchers do not convincingly agree on any single definition of mental models, and similarly, the explanation of good mental models is subjective in nature. Yet, good formalizations or visualizations of mental models enable individuals to translate the internal representation in the mind and can help to better understand them individually or communicate them to others to make

decisions and solve problems. Mental models are also dynamic and are continuously updated as people's perceptions and reactions change.

4.2. From Individual to Group Mental Models

The research on group mental models has grown significantly in the last few years. The terms 'group' and 'team' differ by their definition; one would rather talk about team cognition in an organizational context, while in a participatory context group (of stakeholders) mental model is a more appropriate term to use. Still, the growing research on group mental models (GMM) (e.g., Burke et al. (2006)) can provide an additional, more nuanced, perspective on the mental models beyond individual ones. Generally, GMM refers to the shared and organized comprehension of the relevant information about the characteristics of a certain matter (Rutjes, Willemsen & Ijsselsteijn 2019). Shared or GMMs have been extensively discussed in the literature (Fiore, Salas & Cannon-Bowers 2001; Yen et al 2006). Also known as team mental models, they are defined as knowledge structures held by members of a group that help to describe, explain and predict the behavior of the team/group and allow them to coordinate their actions and adapt their behavior (Burtscher & Manser 2012). This mental model construct can play an important role in understanding the thinking patterns of a group and could be used to improve decision-making. Group members can adjust their behavior based on the pooled knowledge and expectations about future actions.

Examples of group success and failure can be analyzed to show that it is crucial for the members to have a mutual/shared understanding of roles, responsibilities, and actions (Daniel & Daniel, 2018). GMM representations can include the tasks that need to be performed and the best mechanisms to carry them out successfully (Carrington, Combe & Mumford 2019; DeChurch & Mesmer-Magnus 2010). Since these models are developed based on group knowledge, they should be accessible by all members (Kiely et al., 2019; Kleinman & Benson 2006; McComb 2008). In large social spaces or discussion forums, GMMs can help participants understand the ongoing conversation by revealing how people think about the topic, in content and structure, and its function. They help discussion groups to visualize and communicate their knowledge benefiting every stakeholder from the group's collective knowledge (Halbe, Pahl-Wostl & Adamowski 2018). In dynamic work environments, employees should be aware of any required changes in work procedures, project requirements, etc., so that all members can contribute equally, fairly, and accurately. GMMs are a crucial tool for

regulating group functionality in an emergency. They also bring an explanatory power to team management and enhance its performance.

Group members can build and share mental models by using several techniques. For example, conducting collective brainstorming sessions during group meetings. This approach may lead to a shared model of the group goals and help to analyze how the members need to work to achieve them. Moreover, there is software available today (e.g. Mental Modeler (Gray, Cox & Henly-Shepard 2013)) that can be used by all members to explore certain aspects of their group mental models. Exactly like individual mental models, team or group-based mental models dynamically evolve because of internal or external inputs, such as new experience and knowledge. As discussed by Delugach et al. (2016), the efficiency and appropriateness of the formation, refining and updating in GMM, requires active participation of all group members where the information integration, transparency, shared values and mutual understandings are the key. Models can be inappropriate in how they represent a concept due to inaccurate conceptual level and shared ideas leading to incoherence between team members. However, generic causes like not having a common first language, cultural differences, emotional and social barriers, etc. are also relevant (Paynter et al. 2019; Morris, Yorkston & Clayman 2014).

4.3. The Mental Model Creation Process

Every individual develops their own mental model to integrate and understand the procedures of the surrounding world. According to Biggs et al. (2011), the structural properties of the mental model are formed by the social, cultural and environmental factors of individuals where the previous experience of accomplishment and failures have a major part. The social and cultural aspects of any individual shapes their thought process and perception. The perception or point of view to a particular process is a fundamental factor of constructing a mental model. As explained by Rook (2013), a particular process or concept in real world could be perceived entirely differently by two persons from distinctive socio-cultural origin. Therefore, for those two people, the very core nature of the mental models for a particular process or concept would be completely different. Experience can also shape the design of the mental model using trial-and-error learning mechanism. It is a cognitive assessment of success and failure to obtain the desired outcome through involvement in or exposure to that thing or event. After attempting a new thing/action, the human mind tries to link the experience with their previous patterns of

understanding the process connecting to their existing mental models. If the experience does not fit the previous mental model, the mind uses the experience to reform or update the mental model in a way so that the new experience can be justified by the new model. According to Lynam et al. (2012), human psychology suggests that humans have a strong tendency to only accept the information that suits the preformed model and deny the information that does not match with the pre designed/existing mental model. Therefore, major changes in the mental model do not occur rapidly and mental models may need multiple failures to adjust to the new experience.

Language can also have a strong influence in the development of mental models. According to Grenier & Dudzinska-Przesmitzki (2015), the linguistic structure creates the cardinality or dependency of a component on other components in a mental model. Since, the cardinality and relation of different components of mental model is one of the most essential parts of mental modeling, the language can change the formation of mental model as well as alteration of mental model. The process of altering the mental model through experience or editing the structure partially through gaining knowledge or experience, is called refining. Therefore, language differences and boundaries can have a significant impact on the forming of the mental model as well as on the refining of the mental model. People of different languages can have different mental models of the same landscape.

Along with forming and refining the mental model, sharing them is also a major factor. Through sharing a mental model, a person helps others to conceptualize a particular process or topic. Sharing knowledge is also a major part of co-creation of mental models in a socio-cultural environment where the verbal and nonverbal communication is the key. Sharing the mental model completely or partially within a group is important for creating a mutual understanding and improving collaborative decision-making. In accordance with the conceptualization of Maynard & Gilson (2014), it can be said that the participatory mental model is very useful for multi-stakeholder conversation, where all individual participants share their mental model partly or completely with each other to develop a mental model in a collective way. The conversation represents the collectively developed mental model to a degree to which a common conceptualization of an issue exists. As explained by Gray, Cox & Henly-Shepard (2013), a mental model is rarely shared completely. However, sharing even

parts of a mental model helps others to update or refine their mental models partially with the new concepts and knowledge.

The shared mental model, which then becomes a GMM, is developed through multiple iterations in discussions and conceptualizations within a group. This collective construction of mental models is a basis for shared understanding and joint action which is essential for effective decision making. As noted by Grenier & Dudzinska-Przesmitzki (2015) language and socio-cultural views are major factors that help individuals to share their mental models with one another. It is much easier to share mental models within one socio-cultural and lingual group. When socio-cultural gaps or language barriers are present, the misinterpretation and misunderstanding is more likely to occur disrupting the process of refining and updating mental models. Figure A1 represents the general process of formation, refining, and updating of mental models. First, a person gains experience from the external environment, and then develops a strategy to form or modify the relevant mental models. Suppose the person has prior experience regarding a phenomenon that is not entirely new. The person compares the past information to the recent experience, which may lead to an update in the mental model. When a decision should be made, the rules are based on the available mental models, which leads to further decisions and actions and causes new interactions with the environment. This in turn may require a reassessment of the mental models.

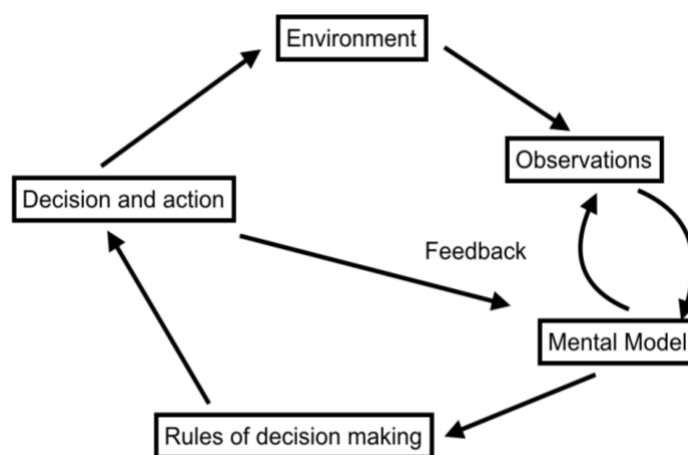


Figure 4.1. Process of formation, refining, and updating of a mental model

On the one hand, quantitative methods are used for analyzing mental models; they can easily deal with large data samples. However, they cannot capture any information regarding emotions, which is a very important factor in the case of mental

models. These studies are unable to account for how social reality is produced and maintained, or how individuals understand their own and others' activities (Blaikie 2007). On the other hand, qualitative analysis can capture the emotions, but it is usually time-consuming, and can be influenced by the biases of the researcher performing that analysis. According to Silverman (2011), qualitative research methods occasionally overlook contextual sensitivity in favor of focusing on meanings and experiences. For example, a phenomenological method aims to discover, analyze, and comprehend the participants' experiences (Tuohy et al. 2013; Wilson 2014). Also, there is only a limited means to extrapolate the findings to other applications (Flick 2014). Using combined or mixed methods can lead to an increase in complexity.

5. Exploring gaps in mental model elicitation, analysis and representation

This section reviews the qualitative and quantitative techniques used for elicitation, analysis and representation of mental models. Additionally, existing gaps in the literature are discussed.

5.1. How to elicit mental models

The most usual techniques used to elicit mental models are survey, interview, online data gathering, video recording, voice transcription, and reflection (Vitharana, Zahedi & Jain 2016). A **survey** is a method where many participants are approached regarding a particular topic and asked different questions. Responses can be structured to help further analyze and quantify the information collected (multiple choice responses, Likert scale, etc.). With an **interview** we can collect exploratory as well as descriptive data. In the interview process the respondents can share their thoughts as per their perspective without any predetermined guided structure or alternative choices. According to Jones et al. (2014), an interview is a more interpretive approach to collecting data than a survey, which allows more in-depth data collection and exploration. By recording the performance of a group of people we can create **videos** that can be further analyzed to measure the behavioral, cognitive, and psychological attributes of participants through different parameters of their interaction among themselves and with their surroundings. Voice recordings are also useful for descriptive and exploratory data collection where a more in-depth interpretation is required from a smaller group of people. Shadbolt & Smart (2015) discussed that a voice recording is a more advanced method of textual interview that

allows to perceive the expression of the person through monitoring modulation of tone as an additional advantage over textual representation of an interview. Using the internet is a very modern method of data collection, where social media posts, comments, shared messages, and online group discussions are used to produce data. These and other tools and techniques have been applied in different disciplines to elicit mental models. Examples include organizational research (Shakeri et al. 2021;), education (Beggiato & Krems 2013; Chan & Black 2006; Gadgil, Nokes-Malach & Chi 2012), risk management and communication (Morgan et al. 2001), and human-computer interaction (Raghupathi & Benbunan-Fich 2020). Based on these studies, two features of the elicitation procedures can be identified: locational (situated or non-situated) (Pommeranz et al. 2012) and methodological (oral or verbal) (Grenier & Dudzinska-Przesmitzki 2015; Jones et al. 2014).

- **Location of elicitation: Situated vs. non-situated procedures of elicitation**

Situated procedures of elicitation are designed in a manner that the location in which the procedure is carried out corresponds to the phenomena to be elicited (Jones et al., 2014; Abel, Ross & Walker 1998). In other words, situated procedures take place in a setting that can be linked to the phenomenon under discussion. For instance, to inquire the respondent about their experience with a facility in their school interviews are conducted within the premises of the same institute. Non-situated elicitation procedures are carried out by removing the person from any kind of locational cues of the phenomena that are considered (Jones et al. 2014). In many cases, mental models are elicited in locations that are convenient for the interviewer or the interviewees and are non-situated. The comparison of locational context allows understanding how the physical context can impact the mental models and their elicitation.

- **Methodology of extraction: Oral vs. visual**

Oral techniques of mental model elicitation use oral tools like word association and semantic proximity in language. These elicitation techniques are preferred by many researchers (Carley & Palmquist 1992; Elsayah et al. 2015; Jones et al. 2011) as a verbal structure can be a complete representation of a cognitive structure of a particular concept and can be extracted from text (e.g., interview transcript).

Language can be seen as a window through which we can understand the conceptual structure of an individual's mind (Batlolona & Souisa 2020; Elsayah et al. 2015; Wijker 2021). Many researchers prefer oral techniques of mental model

elicitation over others (Elsawah et al. 2015; Jones et al. 2011). The verbal structure can be a complete representation of a cognitive structure for a particular concept and can be extracted from interview transcripts. However, some researchers claim that linguistic structures are not capable of representing a mental model completely without incorporating pictorial or image-based approaches (Blair & Buytaert 2016; Jones et al. 2011; Kearney & Kaplan 1997; Tanguy et al. 2014). The combination of oral and visual elicitation procedures allows the collection of two distinct types of data to connect concepts into a complete mental model. Embedding a visual task into an oral interview can help with collecting in-depth information. At the same time, participants can think widely beyond the verbal limits and explore new horizons of their experiences and thoughts (Umoquit et al. 2015). Examples of visual tasks include discussions about pictures, mapping exercises like concept maps, mind maps, relational maps, etc. (Bravington & King 2019; Conceição, Samuel & Biniecki 2017). Table 4.1 summarizes the applications, benefits, and limitations of various techniques.

5.2 How to analyze mental models

Analysis is the process of evaluating the accuracy of mental models in representing a particular phenomenon. It is a complicated and indirect process that requires adjustments for each specific task and teams under investigation. Due to the context-dependent nature of GMMs, there is no well-developed baseline methodology for assessment (e.g., Cooke, Salas, Cannon-Bowers, & Stout, 2000; Langan-Fox, Code, & Langfield-Smith, 2000). It is to be noted that suitable team cognition metrics should capture cognitive content, as well as cognitive structure (how concepts are organized in individuals' minds). The evaluation process can use quantitative, qualitative, or mixed-method techniques. Qualitative analysis techniques include exploratory discussions, focus groups with experts, interviews, etc. (Carley & Palmquist 1992; Sinkovics 2018; Vaismoradi & Snelgrove 2019). Pairwise rating (e.g., Randall et al., 2011; Zhou & Wang, 2010) and concept mapping (e.g., Burtscher, Kolbe, Wacker, & Manser, 2011; Pearsall et al., 2010) are the two main quantitative techniques in measuring mental models. In the former method, the similarity between pairs of concepts is rated, whereas in the latter method concepts are organized in a hierarchical structure.

According to Langan-Fox, Code & Langfield-Smith (2000), Multidimensional Scaling (MDS) system and Distance Ratio (DR) formula can approximate the semi-

metrical data as per their configurations and interconnections using a dependency coefficient. DR formula measures the similarity, differences, and distance between two concepts as a part of the entire mental map. Various pathfinder algorithms can find the shortest path between the components of two maps using distance and distance ratio measures in order to estimate the dependency coefficient. Mohammed et al. (2017) suggested that for measuring performance of a GMM or predicting its capabilities, quantitative analysis and representation methods are more effective than the qualitative methods. Table 4.2 highlights several techniques for analyzing mental models.

Table 4.1. A list of mental model elicitation techniques, applications, and limitations

| Technique | Description and applications | Advantages | Limitations | Used for Individual mental model | Used for GMM | References |
|--------------------------|---|---|---|----------------------------------|--------------|--|
| Interviews | <ul style="list-style-type: none"> - Gathering raw verbal data that can detail the interviewees' experience, and views regarding a topic. - Both situated and non-situated. | <ul style="list-style-type: none"> - Flexible enough to analyze non-verbal cues. - The interviewer can dynamically alter and control the order and selection of the questions according to the situation. | <ul style="list-style-type: none"> - Time-consuming and costly. - Can be biased both on the interviewee as well as the interviewer parts. | ✓ | ✓ | (Cooke & Rowe 1994; LaMere et al. 2020) |
| Cognitive interview | <ul style="list-style-type: none"> - Interviewing eyewitnesses and victims about what they remember from a crime scene. - Mostly non-situated. | <ul style="list-style-type: none"> - Reduces the chance of response error that mostly occurs because of alternative interpretations of questions. - It can be used to elicit a team mental model directly through group discussion. | <ul style="list-style-type: none"> - Time consuming and costly. - Requires special training for the interviewer to use this method. | ✓ | ✓ | (Carbone, Campbell & Honess-Morreale 2002) |
| Verbal protocol analysis | <ul style="list-style-type: none"> - Participants think aloud while interacting with the system. - Non-situated. | <ul style="list-style-type: none"> - Appropriate for studies that verbalization is a natural part of the thinking process. - Particularly useful for completion of unfamiliar tasks. | <ul style="list-style-type: none"> - Labor-intensive process. | ✓ | | (Blackman 1988; Harper & Dorton 2019) |
| Visual card sorting | <ul style="list-style-type: none"> - Participants use cards to define similarity and nominate features of the objects they consider relevant. - Non-situated. | <ul style="list-style-type: none"> - Quick and easy-to-administer. - Allows participants to judge the relevance of concepts instead of relying only on expert opinion. | <ul style="list-style-type: none"> - Relies on feature mapping so may only represent the information that is stored in the short-term memory. | | ✓ | (Doran, Böhm & Hanss 2018; Harper & Dorton 2019) |

| | | | | | | |
|--------------------------|---|--|---|---|---|---|
| Brainstorming | <ul style="list-style-type: none"> - A controller or moderator defines some questions or cues that members of a group discuss and suggest solutions. - Both situated and non-situated. | <ul style="list-style-type: none"> - Easy to understand, inexpensive, graphical representation of ideas. - Encourages out-of-the-box thinking and generates ideas and solutions easily. | <ul style="list-style-type: none"> - It can become self-contradicting, because of the diversity of ideas. Thus, it is difficult to analyze. | ✓ | ✓ | (LaMere et al. 2020; Langan-Fox, Code & Langfield-Smith 2000) |
| Focus Groups | <ul style="list-style-type: none"> - Discussions by experts to gather subjective information by use of open-ended questions. - A verbal/oral technique also capturing some visual data. - Both situated and non-situated. | <ul style="list-style-type: none"> - Capturing non-verbal cues. - Optimal in terms of time. - Flexible discussion. | <ul style="list-style-type: none"> - Moderator bias can influence the discussion. - Expensive because require expert time. | ✓ | ✓ | (LaMere et al. 2020; Massey & Wallace 1991) |
| Pairwise rating | <ul style="list-style-type: none"> - Identifies whether two paired concepts are similar, dissimilar, or identical. - Focuses on the team networks and finding the relations within the team members. - Non-situated | <ul style="list-style-type: none"> - Assigns priorities to the multiple available options and compares alternatives in pairs. - Time efficient, requires little reading or writing (concept pairs can be read out to participants), and is indirect. | <ul style="list-style-type: none"> - The repetitive nature of pairwise ratings can induce a response set. | ✓ | ✓ | (Mohammed et al. 2015) |
| Questionnaires / surveys | <ul style="list-style-type: none"> - Collecting answers to a set of questions about the system at stake. - Suitable for objective data collection in cases where data is to be collected from a larger group - Both situated and non-situated. | <ul style="list-style-type: none"> - Allows a very specific and measurable data collection - Responses of participants can be guided by providing options or alternatives | <ul style="list-style-type: none"> - Response may be erroneously interpreted. - Answers may be dishonest. - Difficult to capture feelings and emotions. - Questions may be misunderstood or misinterpreted. | ✓ | ✓ | (Saad & Dawson 2018; Sharma & Pandey 2013) |
| Graphical Elicitation | <ul style="list-style-type: none"> - Using any graphic or picture of an individual's mental model. - A method of graphical elicitation in which an applicant draws or | <ul style="list-style-type: none"> - More suitable for low-literacy individuals while more mentally demanding than the other methods. | <ul style="list-style-type: none"> - Context-specific and does not provide wider information. | ✓ | ✓ | (Kausar et al. 2010; Mollá et al. 2018) |

| | | | | | | |
|---|---|---|--|---|---|--|
| (Author generated) | creates his or her own mental model without the aid of software programs. - Non-situated. | | | | | |
| Graphical Elicitation (Computer generated) | - Any graphical method using a software to create an image of a person's mental model. - Non-situated. | - Graphs can be generated semi-automatically, avoiding the tedious effort of manual design. | - Context-specific and does not provide wider information. | ✓ | | Kausar et al. 2010; Mollá et al. 2018) |
| Hybrid Elicitations | - A mix of both verbal and graphical techniques. - Photo ethnography is most often related to participatory action research, where members use cameras to document the needs or issues presently fronting their community. The method asks members to externalize their mental models by teaching an imaginary colleague how to solve the problem specified in the given teach-back question. - Both situated and non-situated. | - A purposeful way in which members carefully recognize the means and cycles they will use to show to the imaginary colleague. - It can assist with uncovering many secret parts of a mental model that different techniques might miss. | - Response may not be interpreted as intended by the respondents. | ✓ | ✓ | (R. S. Grenier & Dudzinska-Przesmitzki 2015) |
| Ordered Tree | - Contains nodes (elements) which are ordered according to a specific criterion. Often it is a binary tree, i.e., nodes have at most two participants (conveniently called the left and right child). - It involves recalling the concepts (regarding issues being discussed) from different starting points. - Both situated and non-situated. | - Uses an algorithm to efficiently build hierarchical information and cluster data according to a specific subject. - It provides a more complete representation of the mental model. | - The technique is limited by its reliance on retrieval processes. | | ✓ | (Harper & Dorton 2019) |

5.3 How to present mental models

Mental models can be presented using a variety of techniques (Pérez-Teruel, Leyva-Vázquez & Estrada-Sentí 2015), including concept or semantic maps, ontologies, fuzzy cognitive maps, and spatial maps (see Table 3). Content analysis is used to analyze the core components of a mental model based on their priority, significance, and dependency. Procedural mapping is a very common method of presenting a mental model through process flow, similar to flow charts. Instead of presenting a model as a map, the procedural mapping is used presenting the components within a particular topic or landscape based on their cardinality and dependency. According to Pantförder, Schaupp & Vogel-Heuser (2017), procedural mapping allows to represent both components of mental model and their interconnection, which is more effective and structure elicitation process than cloud content analysis. Procedural mapping cognitive mapping is also the presentation of the components and their interconnection. The Fuzzy Cognitive Mapping focuses more on cognitive perception and its interpretation of finding cause and effect relationship within different components rather than informational dependency within different components (Gray, Cox & Henly-Shepard 2013). Fuzzy Cognitive map shows the components, the relation within the components with the positive or negative association and degree of association. Concept map presentation however is based on a non-directional distribution of components where the cardinality and degree of associations are not presented. Concept maps often form a tree structure presenting the relations between different components as a hierarchical distribution.

Some of these forms (i.e., cognitive, concept, and semantic maps) are quite similar. For example, cognitive maps appear to be the most generic term as there are no strict rules on how to create them or in which context to use. Concept maps deal with more refined themes (e.g., one can use phrases in cognitive maps whereas here the focus is on concepts related to the topic). Semantic maps, in turn, focus on depicting relations between concepts.

Semantic maps are useful for presenting various concepts and their meanings. They are maps or webs of words built to show relations among words or phrases. A

comprehensive review of semantic map mental model representations is discussed in Georgakopoulos & Polis (2018).

Mental models are often described as "sloppy" or "messy." The causal maps, for example, often include gaps or omissions leading to dead ends; signals of correlations between variables are frequently vague; and variables are rarely defined quantitatively. They are inadequately recreated in the mind, owing to the mind's inability to compute or infer the implications of relatively simple situations. This lack of completeness and consistency complicates mental simulation.

When mental models are updated with new knowledge, the old information is not immediately lost; rather, it remains in memory alongside with the new information, and may still impact decision making. The boundaries and contours of mental models are "fuzzy," that is, they are ill-defined and readily changed. This is related to the nature of human memory, in which mental models are linked to other information in a complex network of relationships. Important feedback processes are often left out of mental models. People prefer to adopt an "open-loop" view in which one event leads to another in a single causal chain that is unidirectional because it follows a fixed schedule, rather than a closed-loop perspective in which actions generate consequences that feedback to inform and modify decisions.

These techniques are summarized and compared in Table 4.3.

5.4. How to address gaps in mental model

We developed a systematic, automated, and impartial tool named Discussoo (Anjum et al. 2021) that can help to extract mental models from online discussions. This tool relies on the analogy of GMM elicitation with the process of developing integrated understanding of different topics while engaging in discussions in real-time. After the digital revolution, smart technology and the Internet have become a major part of everyday life, so it makes much sense to explore how digital technology can help to improve our understanding of mental models. Li (2007) showed how users' search pattern, fetched from different web search engines, can be inferred as their mental model of a searched topic. These mental models appear from collecting the searched data about a particular matter, including the topic, context, similar and interconnected

words/phrases. The study demonstrated that understanding the search pattern through a mental model of the topic can help to improve the suggestive search in future along with improved searching speed and efficiency.

Table 4.2. A summary of mental model analysis techniques, their advantages, and limitations

| Technique | Description | Advantages | Limitations | Reference |
|--|--|--|--|--|
| Quantitative | Methodical examination of the quantifiable data which requires the usage of statistical and mathematical instruments. | Larger samples can be analyzed. | Emotional information cannot be inferred. | (Kelle 2006; Rahman 2016a; Ramona 2011) |
| Qualitative | Techniques are based on non-numeric analysis, descriptive and textual or content-based evaluations. | Emotions and attitudes can be captured. | Time-consuming and depends on the biases of the researcher. | (Kelle 2006; Rahman 2016b; Ramona 2011; Wenger 1999) |
| Combined/ Mixed | Gathering both qualitative as well as quantitative knowledge about the system at stake. | Can combine the advantages of both qualitative and quantitative approaches. | Complexity is high and can be overwhelming. | (Malina, Nørreklit & Selto 2011) |
| Multidimensional Scaling (MDS) and Distance Ratio (DR) | Analysis performed using a pairwise rating eliciting method to produce positive and negative interactions in concept pairs. Used for measuring causality between variables. Identifies how concepts are organized in an individual's mind. | Used for studying complex networks e.g., self-loops where variables are interacting with themselves. Improves collaborative decision-making in within a group through incorporating cognitive content and structure. | Hard to translate and visualize as maps of various types. As the matrix expands, it can become difficult to understand. | (Mohammed et al. 2017) |
| Content analysis | Analyzes the core components of a mental model based on their priority, significance, and dependency. Words or phrases are extracted from text and are further classified to represent the main concepts in the text. For inferring the relative importance of each concept. Statistical modeling is used. It is a systematic method for analyzing written statements such as formal speeches and transcripts of interviews. | Used to determine the presence of certain words, themes, or concepts within some given qualitative data High in reliability as it follows systematic procedures to be replicated. Unconstrained by the availability of respondents. | Likely to have incomplete representation at the end as respondent might not be available for clarification. | (Langan-Fox, Code & Langfield-Smith 2000) |

| | | | | |
|--------------------|--|---|--|------------------------------|
| Consensus analysis | <p>This method is used to identify the extent of sharing of concepts, information, and knowledge among individuals as this method is mainly designed to identify the overlap in responses or shared understanding among participants.</p> <p>Designed to investigate the distribution of cultural knowledge among a given group of people.</p> | Can produce a high level of statistical confidence with small sample sizes (4 to 30 individuals). | Can only measure the quantitative data as it relies on statistical analysis. | (Stone-Jovicich et al. 2011) |
|--------------------|--|---|--|------------------------------|

Table 4.3. A comparison of mental model representation techniques

| Technique | What is it? How is it used? | Advantages | Limitations / Disadvantages | Reference |
|--------------------------|---|---|--|---|
| Concept Map (CP) | <p>A network in which nodes represent ideas connected by named, directed edges that show how they relate to one another.</p> <p>Directed edges indicate the relationships between concepts.</p> | Simple visualization of a system, displaying relevant concepts, and the relationships between them. | <p>Can be time consuming.</p> <p>Provides limited detail about meaning and relationships between concepts, which can lead to ambiguities.</p> | (Conceição, Samuel & Biniecki 2017; Yoo & Cho 2012) |
| Procedural mapping (PrM) | Characterizes the implicit and explicit procedures used by a participant to perform a given task, for example characterizes the range of decisions that individuals might make as they engage in each activity. | Provides a richer understanding of the processes in which participants engage. | Focuses on the task domain rather than on the system at stake and individuals or groups involved. It tells us little about the general knowledge that individuals might have about the system. | (Kolkman, Kok & Veen 2005) |
| Semantic Map (SM) | A cognitive approach that categorizes and organizes information in a graphic or visual way. A word or concept is connected to other words or concepts that are related to it in some way. | <p>Semantic maps improve rational thinking and the creation of links between words representing concepts.</p> <p>Helps to classify, relate, and arrange thoughts.</p> | It is difficult to integrate all the concepts related to a phenomenon in the form of words and their relations. | (Georgakopoulos & Polis 2018; Regier, Khetarpal & Majid 2013) |

| | | | | |
|---------------------------|---|---|---|--|
| Rich picture (RP) | Communicating complex ideas and concepts by using pictures, drawings, and text. | Presents the whole system at once, even if only peripherally, helps to identify patterns across the system to focus on the most important elements. | There is a lack of universal standards, for interpretation of art and rich images, which makes it hard to further generalize and analyze Rich Pictures. | (Bell & Morse 2013) |
| Causal-loop diagram (CLD) | Conceptually represent dynamic systems demonstrating how variables (such as causes, issues, and processes) interact and influence each other. | Useful for identifying high and low leverage intervention points in a system, as well as revealing the system's underlying feedback loops. | Can be difficult to understand. Represents associative but not semantic changes in information about conceptual relations. | (Haraldsson 2004) |
| Fuzzy Cognitive Map (FCM) | Graph structures used to represent causal reasoning in the form of digraphs consisting of nodes and weighted edges. Similar to CLD but interactions have weights assigned to them indicating their relative importance. | Can represent weak and hazy relationships. | As with other techniques, hard to incorporate uncertainty. Sometimes erroneously seen as dynamic and evolving. | (Gray, Cox & Henly-Shepard 2013; Pérez-Teruel, Leyva-Vázquez & Estrada-Sentí 2015) |

Huang et al. 2016 suggested that online discussion-based learning processes are very effective to develop a shared mental model, where participants can share their thoughts and understanding about a topic and gain mutual knowledge (2016). For example, online discussions can facilitate teamwork in the classroom as they help the students to develop a team mental model for a particular assignment or learning task.

Discusoo is an online discussion forum for users to share their knowledge, perspective, experience, and opinions about a particular topic. Users can choose among various topics discussed or questions to answer or problems to debate. They can also formulate a new topic or problem statement or question and share it in a post which all authorized users can see and share their thoughts on the topic by submitting comments under the post. All these comments, discussion statements, argumentative statements and other raw textual information in the discussion forum is the source of data collection, which happens in real time, meaning that each and every second the database of the platform is refreshed and updated with new information shared in the platform by the users. Discusoo addresses some of the identified gaps in literature related to elicitation, analysis, and presentation of mental models, briefly described in Table 4.4. Figure 4.2 shows different methods and techniques used in this tool for each phase of mental model formation. Its functions/modules address all three stages of mental model extraction, including elicitation, analysis, and representation.

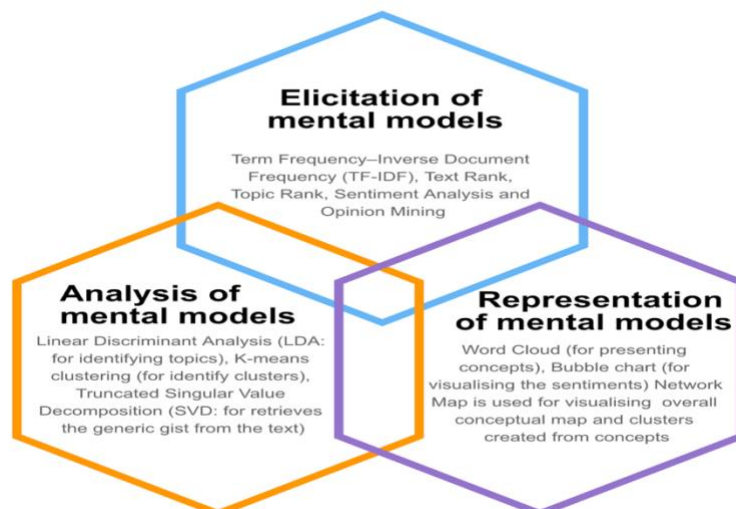


Figure 4.2. Techniques used in Discusoo for each phase of Mental model formation

Table 4.4. A list of identified gaps in mental model elicitation, analysis and presentation that are addressed by Discussoo

| Mental model gap | How Discussoo addresses it |
|--|--|
| Most techniques in mental model elicitation rely heavily on how the interviewer has interpreted the participants' responses, which can introduce biases. | Instead of conducting the discussion and soliciting ideas, opinions and data first, and then moving to assemble this information in a form of a conceptual model, we generate the model 'on the fly' with AI algorithms running in the background and processing the comments as they are posted. Assuming that the used AI algorithms are neutral, we can avoid the interpretation biases that facilitators and moderators may introduce. |
| Mental model elicitation process can be time-consuming and costly. | Instead of requiring stakeholders to be at a certain location for a certain time to conduct a workshop and exchange knowledge about the problem, Discussoo offers an asynchronous remote mode of participation when attendance can happen at any time and from any location, where they can get online and join. Discussoo may replace multiple workshops and can support the discussion asynchronously. There are no limits on the duration of the discussion as it is online and free of charge. |
| In the analysis phase combined or mixed methods can be complex and time consuming. | Discussions are analyzed in real time, using a combination of techniques and methods to deliver a comprehensive analysis of text data. |
| Most of the quantitative methods used for text analysis do not capture emotions, which is a very important factor in the case of mental models. | Discussoo can capture information regarding emotions. Sentiment analysis distinguishes between positive, negative, and neutral comments. |
| There are several techniques for representing mental models but most of them are hard to understand for those stakeholders who are not experts in the field. | Results are represented as interactive visualizations, so that users can easily interpret the outcome of a discussion or group decision making. Visualizations used include word clouds for concepts, sentiment analysis for polarity and network diagrams for overall conceptual model so that users can interact with the graphs and get more engaged in the discussion. |

For improving the analytical capacity in this tool, we leveraged social media data analytics. It is a very effective technique for mining data about a particular group of people through using their shared information in social media such as comments, posts, multimedia contents, shared messages and online discussions (Fan & Gordon 2014). Social media data analytics techniques are used for business intelligence while analyzing consumers' behaviors, their needs, preferences, convenience, and other factors. Another technique used in Discussoo is opinion mining, which is a natural language processing and text analysis techniques used for mining and interpreting the social media data (Bakshi et al. 2016). The sentiment analysis is then done by using computational linguistics to identify subjective information from the clustered information from sources. Topic modeling is another relevant AI technique that

analyzes and processes the texts to find a topic for a bunch of clustered text data segmented by different subdomains of sentiment and relational patterns. [Arora et al. \(2013\)](#) as well as [Lawrence & Reed \(2015\)](#) discussed that the topic modeling technique used natural language processing (NLP) to interconnect phrases, text sets with subjective relations for finding the context behind the text map. As an NLP technique, the argument mining process has a distinctive advantage. It can process the texts and find the topics and interconnection between subjective variables through analyzing the argumentative statements.

6. Exploring mental models with Discussoo: Australian community energy case study

We demonstrate the functionality of Discussoo using the example of a case study where a group of social science researchers, renewable energy companies, and a local community collaborated on a project related to community energy in an Australian rural area. A discussion was created in the platform for the project and participants were invited to join and share their ideas and information related to the topic of the project. We started with the following questions: (1) which groups of stakeholders should be targeted for energy transition, (2) what the preferences, financial and behavioral considerations of energy users are, (3) how the broader community can benefit from the energy transition. Nine participants participated in this discussion and there were more than 70 comments posted¹. Following, we explain how each stage of mental model creation is implemented in practice.

6.1. Opinion collection and stakeholder engagement

For eliciting mental models, we have invited all the project stakeholders to participate in the discussion going on in Discussoo. Using AI and advanced analytics, the digital texts are immediately processed to extract additional information, detect patterns in the data, and present meaningful outputs in the form of mind maps (conceptual models). These techniques include Information Extraction (IE) and, most importantly, NLP to identify and analyze useful, structured data. NLP makes it easy to extract key concepts, major keywords, relationships between them, and the interactions to draw mind maps for the discussed topic. The goal of the tool is to create

¹ The discussion can be seen at <https://discussoo.com/discussion/68/detail>

TF-IDF appears to be the best technique for extracting the concepts from the comments, while Topic Rank techniques appear to be the most helpful when extracting topics from unstructured data. Most elicitation techniques rely heavily on how the interviewer interprets the participants' responses and can only capture the information that is expressed verbally. It can be time-consuming and costly, allowing biases to seep into responses at the end. Discussoo can avoid interview biases by replacing humans' judgements with algorithms to analyze responses. Normally in interviews interviewees are affected by their environment but in this platform, everyone can express their mental models comfortably while participating in online discussion. They have an option to express opinions and comments anonymously. It is not time consuming to analyze the data and participants can join the discussions at any time, at no costs.

6.2. Discussion analysis

After the concept extraction, to analyze the data (i.e., unstructured comments), Discussoo identifies and groups relevant concepts into a cluster and then assigns a representative topic to each of them. For example, concepts like *Fossil Fuels*, *Bushfire*, *Ozone layer*, *Greenhouse Gas* will be added in one cluster and the topic is assigned as ***Climate Change***. Multiple algorithms are used on this data to select the one that creates the most meaningful clusters with high intra and inter-cluster similarity, the details of which are discussed below. Linear Discriminant Analysis (LDA) is a popular technique in NLP for topic modeling. However, some problems were identified with the use of this algorithm. For example, it is not suitable for short text fragments as in Discussoo, where we are often analyzing comments which contain 3-4 sentences on average. K-means clustering is another clustering technique that is limited to merely grouping of the concepts and does not cater to the topic assignment. There were still some limitations, such as difficulty in determining the ideal number of clusters, and repetition of words within the clusters.

Truncated Singular Value Decomposition (SVD) is a dimensionality reduction algorithm that helps derive topics from the main text. It is based on an abstractive approach that retrieves the generic idea from the text. This algorithm can generate topics from the posted text and comments that were further used to cluster the concepts extracted. The clustering is based on the semantic similarity of the concepts.

The clusters obtained and labeled are closer in terms of semantics. However, there is still room for improvement which can be achieved by tightening the concepts selection criteria. For capturing information regarding emotions, we are using sentiment analysis which is a very important factor in the case of mental models. Sentiment analysis is a highly associated process with opinion mining. After creating the opinion summary through cauterization of keywords and concepts, the sentiment analysis starts to classify the keywords and concepts through various subjective parameters. The classification process is done by using the predetermined classification names or topics such as political statements, scientific statements, social statements, personal opinions and others. The clustered interconnected keywords are then analyzed under the specific class through using ordinal parameters such as positive statements, highly positive statement, negative statement, highly negative statement, and others. A number of unsupervised approaches such as TextBlob Sentiment, HuggingFace sentiments etc. were tried and tested, where HuggingFace seemed to work better.

Instead of using one technique for analyzing user's comments inferred as mental models, in Discussoo several techniques are deployed to deliver a comprehensive analysis of text data. Unlike the other quantitative methods, it can capture information regarding emotions using sentiment analysis which is a very important factor in the case of mental models. Usually combined or mixed methods can lead to an increase in complexity but in the case of this tool all the discussions are being analyzed in real time so it can save time as well.

Figure 4.4 shows sentiments extracted from discussion by using HuggingFace sentiment analysis. For each comment it identifies the sentiment. Output is presented in the form of a graph using bubbles, where green bubbles represent comments with positive sentiments, red bubbles represent the comments with negative sentiments and gray-colored bubbles represent the comments with neutral sentiments. Users can interact with this visualization, once users hover the cursor over the bubble, they can read the full comment. There are several techniques for representing discussion but most of them are hard to understand. We have addressed this issue in Discussoo by representing the results in intuitive and interactive visualizations, such as word clouds for concepts, sentiment analysis and concept maps, so that users can easily interpret the outcome of a discussion or group decision making. Unlike any other mental model

elicitation techniques, here emotions/sentiments attached to comments are also identified.

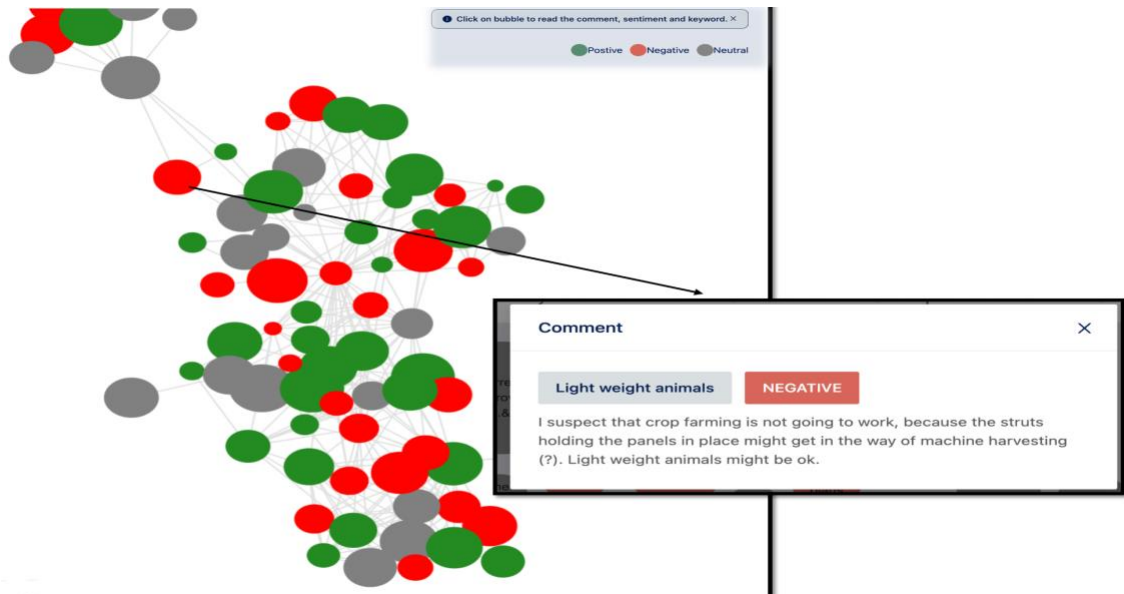


Figure 4.4. Sentiments extracted from the community renewable energy discussion

6.3. Discussion representation

After analyzing, the next stage is representation of mental models. Discussoo updates the visualizations created in real-time so that users/participants can see how the course of the discussion may influence some of the main concepts identified by the algorithms. Various aspects of the mental model are presented using multiple visualizations such as World Cloud, Concept map and a Mind map. These presentations only present the major concepts or nodes of the mental model with their interrelations, while considering their relationships by using directional vectors, links, or arrows. Converting the concepts and topic mappings into a network diagram is the last stage of the mental model exploration that starts with filtration of concepts and topics. After filtering and cleaning the concepts and topics, the main concepts of the posts are extracted and used as topics. Each of the topics further has related concepts clustered with them. The topics themselves are connected to depict a unified relationship (belonging to the same post). If the visualization becomes overlapping and messy, because of the number of clusters extracted, moderators can set a limit for the number of clusters and can delete irrelevant clusters. For the ease of integration and freedom of customization, a visualizer has been used to convert the conceptual map into an HTML format to be easily integrated into the web-based platform. Figure

4.5 demonstrates the conceptual map created by Discussoo for the Community Energy project.

6. Discussion

The process of digitalization has been one of the dominant factors to drive the evolution of our society, with social media becoming an active part of human lifestyle and everyday life. As part of an “always-connected” World, it is estimated that around 60% of the world population is present online at any given time, while a 49% of them are using social media (Hargittai, Piper & Morris 2019).

People are using digital platforms to share their thoughts, perceptions, experience, information, and knowledge in a professional and private context. While from a user perspective such platforms enable the capability to generate and consuming information at a global scale, business stakeholders can use that same information to generate added business value. Information from social networks is a valuable asset also in science and has enhanced the capability of analysis in different fields, especially where the social interaction is critical to gain insight and knowledge (e.g., behavioral science, psychology, economics, education, and sustainability science).

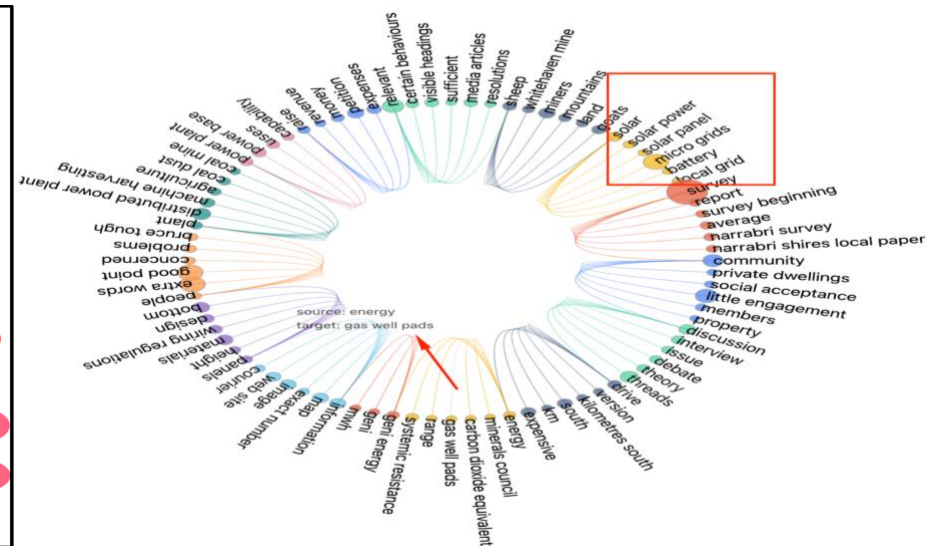
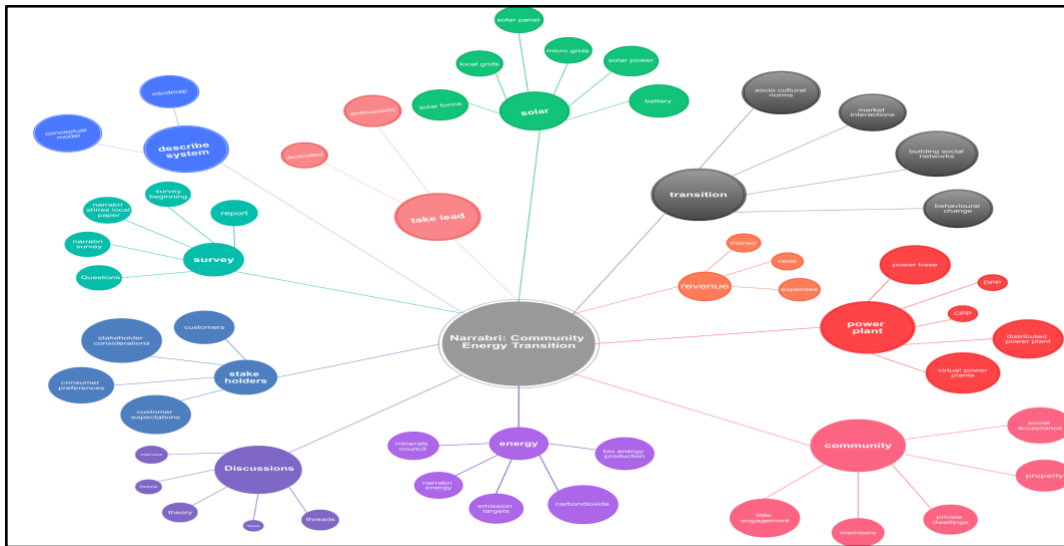


Figure 4.5. The Clusters and the Arc Diagram

The Clusters are generated and presented as a graph by Discusoo (left side, in which each color presents a different cluster, and the size of bubbles represents the frequency of each node). In the Arc Diagram (right side), each color represents a separate cluster of concepts identified in the previous step (e.g., solar, solar power, solar panel, battery, and local grid all belong to the same cluster). The size of the bubble represents the frequency of that particular concept in the discussion.

From a research perspective, understanding and formalizing the mental models adopted by individuals and established within groups that are addressing a task or discussion may lead towards the development of ad-hoc tools to achieve a given purpose. Indeed, once mental models are extracted, they can become objects of analysis to enhance the decision-making process in each application context.

In line with previous works aimed to develop relevant and actionable insights about social-political or scientific issues (Gentner & Stevens 2014; Taghikhah et al. 2022), Discusoo produces a contextualized representation of mental models from online discussions. Mental models are primarily expected to contribute to generating a more focused picture about a particular topic or procedure that can enhance the underlying cognitive process (Huang et al. 2016). With the development of the group mental model structure and by tracking their evolution in time, the socio-psychological researchers and practitioners can also gain more information about the group of people who are participating in the discussion forum.

The ability to represent group mental models from participatory activities can be used in many ways within the broad decision-making field. For instance, in certain cases it can contribute to better defining roles and to mediate in the presence of socio-cultural issues or controversy. They can also help to find the power positions of particular social groups and use them as leverage of positive influence. Additionally, by considering perceptions and behavioral attributes at a group level, the social behaviors of a particular group of people can be better defined and analyzed.

Another key feature to consider it's the possibility to provide real-time support, meaning certain tools may provide valuable information from mental models to users and moderators while the discussion is happening. The real time approach further enhances the role of mental model representation that becomes an active asset within the interactive process. According to Pantförder, Schaupp & Vogel-Heuser (2017), combining the knowledge of a group of experts through using this participatory discussion forum the real time mental model development can be also used to predict the future implication and effectiveness of an innovative idea.

The major limitation of this real-time mental model formation environment is that its credibility and usefulness is very much dependent on the shared information

by the members of the discussion group. Therefore, biased selection of the discussion group can result in a biased mental model. At the same time, the language and socio-lingual perspective is a major barrier in the textual processing and interpretation system. The proposed platform does not have the capability to interpret the intended aspects of a statement made by members of a discussion group by considering their socio-cultural and linguistic background. Wrong interpretation of a statement can lead to an inaccurate development of a mental model, where major subject nodes could be missing or the relational vector and dependency between the nodes could be false. It will also impact the descriptive analysis as well as the predictive analysis of the topic under discussion.

Discusoo is one of the first platforms developed to facilitate effective and scalable discussions between stakeholders through presenting discussion-based mental models using AI techniques. It can contribute to formalizing mental models in the following ways:

- It enables facilitators to understand, analyze and visualize mental models. It presents a structured and machine-processable representation of a discussion in an abstract way summarizing all key knowledge.
- Most elicitation techniques in mental model elicitation rely heavily on the interviewer interpretation of the participants' responses. This can be time-consuming and costly, allowing biases to seep into the process. Discusoo can remain neutral throughout the process.
- In the analysis phase, combined or mixed methods can lead to an increase in complexity. Discusoo analyzes the discussions in real time, which can save time. Unlike other quantitative methods, it can capture information regarding emotions which is a very important factor in the case of mental models.
- Discusoo uses several techniques to deliver a comprehensive analysis of text data. Since most of them are hard to understand for those stakeholders who are not experts in the field, Discusoo uses intuitive and interactive visualizations, such as word clouds, sentiment analysis and network diagrams, to help users interpret the outcomes of a discussion.

Future research is needed to evaluate the extent to which Discussoo informs the discussion and helps to engage stakeholders. So far, we do not have enough statistics to decide which of the support tools running in the background are most useful and how to improve them. In the tradition of participatory research, we will involve stakeholders to decide about additional features and functionality that Discussoo needs, and which aspects of the mental models delivered are more informative and stimulating for the users. Currently, the platform is operational and supports on-line discussions, and, as with all other AI applications, the more it is used, the more data we can collect to train the algorithms and to learn how to best use them.

7. Conclusions

A mental model represents the thought process about the world around us and is used for cognitive, behavioral, knowledge and decision-making processes. Today, digital media and especially social media have become a major part of human lifestyle. People share their opinions, based on their mental models through online discussions, social media, and digital forums. Through identifying mental models from a particular online platform, exploratory analysis, examination, investigations, and predictive analysis can be done and these can be helpful for decision making in any field. We hypothesize that knowing the evolution of the GMM generated during the discussion can also inform and enrich the discussion itself. Our research highlights the application of the Discussoo tool ([Anjum et al. 2021](#)) for group mental model elicitation, analysis, and representation. A detailed review of literature about mental models shows that there is no single agreed definition of mental models. This only means that mental models can be professionally credible only if a reliable process of validation and standardization is in place. This also means that mental models should be constantly checked by the group involved and then improved and aligned with what the people really think. The more transparent and interactive this process of mental model elicitation is, the better the chances to produce a useful mental model. This makes it only more promising to use social media, which allows constant asynchronous stakeholder engagement to generate meaningful mental models. The Discussoo platform offers this functionality, which we demonstrate for the case study on community energy in Narrabri, New South Wales, Australia. The platform can be used in various settings and problem situations, where the steering of collective mental models can improve the functioning, resilience, and sustainability of a social,

environmental, or technical system. We expect that in future, Discusoo can be used by policymakers, commercial organizations, NGOs, etc., who may benefit from a more direct, transparent, and meaningful stakeholder engagement. This study suggests several potential directions for future research. Firstly, we can further refine the platform and the AI algorithms involved as more data becomes available. When coming up with a filtration strategy to clean concepts or key phrases, as with all the machine learning approaches, the more data, the merrier. In future research we can compare an individual's mental model with the group model and analyze the evolution of mental models over time. We can also explore how users will reconstruct knowledge and change their mental models based on their interactions with the mental models produced.

Chapter 5: Reconstructing mental models through a moderated framework for serious discussion

Preamble

Paper Status

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1. Overview

In this chapter have examined the cognitive change in mental models of students and consequently change in their opinion as a result of their participation in an online discussion forum. We had two hypotheses in this research. The first hypothesis is that “Discussoo (a platform for online discussions) can lead to change in mental model of participants”. We tested this hypothesis by conducting an experiment with more than 150 students where they were asked about challenges faced by them during the COVID19 period. Each student was first asked to fill out a survey where they must answer 8 open questions related to covid 19 challenges. After providing their answers

students were redirected to Discussoo (a platform for online discussions) where they participated in the discussion about challenges faced by them during the COVID19 period. After discussion students have filled out the same survey again. We can say that there is evidence of change in the mental models of the participants who have provided new answers to the same questions after they participated in the discussion at Discussoo. More than 60% of students have changed their answers. Our second hypothesis is that “visualizing mental models during the discussion can lead to a better understanding among participants and help them to learn from each other”.

This hypothesis is connected to the functionality that Discussoo provides and, by doing so, helps the participants to learn from the opinions of others. We used the 'ladder of Inference' proposed by Peter Senge as components/steps that lead to reflection/learning. We suggest that the use of Discussoo could assist in 'observing data', 'selecting data', 'adding meanings to the data', 'making assumptions', and 'coming up to conclusions'. For each of these steps, we assigned several statements in the 'after' questionnaire. The participants should evaluate these statements based on the Likert scale (from strongly disagree to strongly agree'). Most of the participants rated statements 1 and 2 as 'strongly agree' which means that Discussoo made information more accessible and eased the selection process"

We also reflect on the results of an experiment where a group of participants interacted with the Discussoo. Based on comparison of the results from pre-test and posttest questionnaires we concluded the following:

- Discussoo can also cause mental models to change and evolve.
- Visualizing mental models during the discussion can lead to a better understanding among participants and help them to learn from each other

2. Abstract

Mental model shift or mental model change is one of the reported outcomes of formalizing group mental models. Many researchers have provided different explanations for these changes. In this paper, we have examined the cognitive shift in mental models of students and consequently change in their opinion as a result of their participation in an online discussion forum. Our hypotheses were (i) Mental model change can occur while users are participating in online discussions using “Discussoo”

(a platform for online discussions) and (ii) visualizing mental models during the discussion can improve communication among participants and help them to learn from each other. We conducted an experiment with 165 students where they were asked about their educational challenges during the COVID19 period. Each student was first asked to fill out a survey, where they had to answer 8 open questions related to covid 19 challenges. Afterwards, the students were directed to Discusoo to have an online discussion about the given topic. After the discussion, students filled out the same survey again. Our findings indicate a shift/change in the mental models of the participants as more than 60% of students have either changed or elaborated their answers. We realized that the functionality of Discusoo helps the participants to learn from the opinions of others via 'observing data', 'selecting data', 'adding meanings to the data', 'making assumptions', and 'coming up to conclusions'.

3. Introduction

A mental model is a representation of the surrounding world, description of an individual thinking process, its many aspects, and a person's intuitive sense of their actions, interactions, and effects (Johnson-Laird 2006). For the simple reason that we can't possibly memorize all there is to know about the world, we rely on models to break down incomprehensible information into more manageable chunks. They impact what we believe and comprehend and form the connections and possibilities we notice. We reason, prioritize, and evaluate information based on our mental models. How well we think depends on the mental models we have available and how well they fit the problem. Nonetheless, most of us are experts in our fields. However, we don't have a network of mental models, but only a handful exclusive to our area. For instance, each professional views various things from different angles. An Engineer will naturally use a systemic perspective. An economist may see incentives differently from a psychologist (Moon et al. 2019). The evolutionary framework is fundamental to the mind of a scientist.

The ecology may be of primary interest to a botanist. At the same time, climate change may be the focus of an ecologist, the health of the trees would be of direct interest to a forestry scientist, and the land's economic worth would be of primary interest to a businessman. By mentally combining these fields or by bringing field experts on one platform for sharing their opinion, we may approach an issue from all sides. One's

ability to see the whole picture of a situation is diminished if just one perspective is considered (Hamrick 2019).

Mental models are subject to change over time. These changes can be in a specific area of personal traits or thinking patterns and/ or a group change (Berger & Luckmann 1966; Zerubavel 1999). The research found that human mental models change with the passage of time through their experience and learning. Therefore, it is said that mental models are dynamic in their nature. Consequently, the researchers in the areas of human-computer interaction (HCI), learning and education, management, and organization have taken an interest to study the mental model dynamics to create new knowledge and apply the findings to improve their relevant industry. Given that our socializing, values, opinions, training, and expertise shape the frames we use to make sense of the world, we may say that mental models are instrumental in making sense of the world. Our worldview is shaped by the mental models we've constructed (Hildebrand et al. 2019). They play a significant role in shaping our information processing and our responses to that processing as presented in Figure 1.

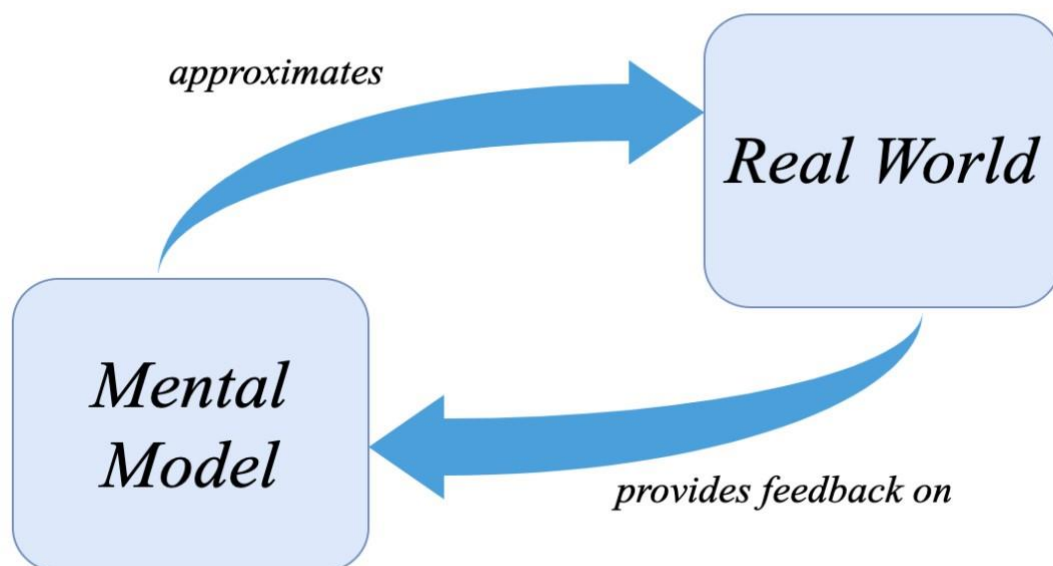


Figure 5.1. Mental models and Real-world consequences

Mental models describe, summarize, predict and lead to behavior in the real world. Real-world consequences of information adaptation (selective effect on viability and on competition among mental models.)

The changes in the mental scheme are dependent on external factors for example human interaction, formal learning, trial, and error, whereas, some research suggest that change in the mental model is not only limited to learning but also based on biological factors such as human mind innate ability (Nersessian 2002). The variations in nature of mental models and related their changes to societies, geography, and culture. In individuals change in their mental model is subject to their desired outcome, if they believe that the outcome is not as they have planned or results are inconsistent over time, then they can consider alternative views/opinions to reconstruct their mental models. However, it is a fact that this change does not work every time, in some cases, some individuals hold their mental models even after destructive consequences arise and their interpretation of their own mental model has been proved false (DeChurch & MesmerMagnus 2010).

Individuals can restructure or change their mental models in different ways depending on their surroundings or the people they engage with. Some of the various ways in which people change their mindset may include studying at school, exchanging views with friends, and doing personal research among others (Kerr, Deane & Crowe 2019). For instance, schooling affects the perception of learners. When people share their views with others about a case study or any given discussion, they become likely to either change their opinion or learn new things. Because of this, when individuals need to cooperate to achieve a shared objective, they must take into account the perspectives of others and modify or compare their mental models accordingly (Díaz-Guio & Ruiz-Ortega 2019). Despite other factors, the media is one of the strong forces contributing to mental model change in different ways. The mental model change by media is spread over several subjects including political thoughts, fiction drama, art and culture, infotainment, and marketing sense (Ferrara, Chong & Duryea 2012). Social media in recent years has emerged as an important tool for mental change and updates. Socio-cognitive theories also support that the activity wherein an individual is more engaged and more interested will create a specific mental model. Therefore, it is evident that the marketing sector and business organizations on the basis of data science are grabbing the public interest to inculcate specific mental change (Deloitte 2011; Hinchcliffe, Kim & Dachis 2012). The associated customer normally inquires for some kind of integrated shopping and quality service experiences largely based on technological interaction built after studying the mental model change (Wuyts et al. 2010).

Changing mental models might be of great benefit to society, businesses or organizations, and even individuals or groups. Businesses benefit mostly by changing/reconstructing mental models. Businesses may improve their economic forecasts by revising their assumptions about market forces. Whenever a company's leadership implements a shift in its functional mental models, for example, staff members can better use such shifts to inform their decision-making (Sokol & Flach 2020)

Mental models enable people to make choices with more alignment, uniformity, clarity, and creative planning (Aminpour et al. 2020). When one shifts their perspective on a problem or case study, they may benefit from the insights of others who have gone before them.

Many implementation strategies like education and training, facilitation, reflection, audit, feedback, etc aim to bring change or shift in mental models (Holtrop et al. 2021). Several scholars have shown that classes may be structured to actively participate in an investigation process in which students collect data, compare and contrast findings, and construct new understanding. The educational software acts as a guide for the pupils while they strive to formulate their responses to the prompts (Bandura 2021). One of the primary purposes of education is to help students construct miniature worlds in which items behave following a set of laws (Daniel & Daniel 2018). Purpose, action, contemplation, and maintenance are all necessary for learning, which involves shifting from an original paradigm to a modified one. According to the notion of cognitive change, knowledge is formed in certain areas, beginning with simple concepts and becoming more sophisticated as we gain more information and experience (Arriaga et al. 2018). In most cases, this shift takes place slowly but steadily, except for instances where the learner can consciously steer their progress using higher cognitive methods. Per the studies in psychology, when we get new information, we evaluate whether or not it fits our knowledge, worldview, and set of values. Discordant evidence may be disregarded or filed away in an obscure section of their extensive knowledge structures. One's learning attitudes may influence how readily one takes in new knowledge. As a result, some studies on mental models aim to facilitate communication to influence outcomes like behavior change by delivering data in formats consistent with commonly held beliefs. Another important question to consider is if people actually change their mental model. In some cases, people do

change their mental models but, in some cases, no they do not as sometimes their deeply held opinions or beliefs are intractable. However, still, we can try to provide information in a way that can facilitate change.

Researchers in this field have paid much attention to "nudges," or manipulations in decision architecture, during the last decade. This category of behavior modification draws on findings from psychology to create settings where individuals are more likely to make choices that benefit themselves and society as a whole (Lane & Dal Cin 2018). Interventions that concentrate on the arrangement and architecture of available options (decision framework) outperform those that focus on the explanation of additional possibilities (decision knowledge) or the reinforcing of behavioral goals across a wide range of cognitive variables (decision assistance). New forms of communication have emerged due to the Internet's pervasiveness in modern life and spread quickly among the population (Edgerton & Palmer 2022). Public media, notably, have developed a universal way of engaging. Platforms like Facebook and Twitter allow users to exchange material and retain linking effortlessly. These platforms provide "one-to-many" broadcasting, making it easy for users to share information.

The mental models are concerned with human and human-related affairs. Therefore, the mental model can be helpful in every walk of life. The prominent research reveals that the following fields are taking massive benefits from the studies of mental change 1) "mental accounting" for capital monetary benefits, 2) mental models for commercial productivity and technology development, 3) mental models for health care and research, and 4) mental models for climate change and protection. Besides this, the historian has given the perspective of development in the modern world and subsequent change in mental model to viewing how this world works. "Shifting to believing we live under universal physical laws rather than divine caprice made it possible for individuals to move from handicrafts to mass production technologies" (Mokyr 2013). As narrated the mental models are helping in making the dynamic decision making in economic development and which also give the structural changes in human lives, therefore, the acceptance of shortcomings in studying the changes can further improve this area (Sterman, 2000). Mental models are relevant in human life as they have a role in decision-making everywhere. For example, making the investment, choosing a child's school, being an effective citizen, etc. The mental

models are impacting the decision-making process by providing the default assumptions. Therefore, researchers emphasized the value of the structured and formal knowledge of an individual or team members while studying a particular mental model to develop any platform (Burke et al. 2006; Marks et al. 2000).

Particularly, in developing team mental models the team members' mental representations of relationships, knowledge, and/ or systems are considered central for successful team adaptation (Burke et al. 2006).

Conclusively, the organization of any walk of life and the development of mental models through any digital platforms can take benefits of mental model change study if they study mental models in their original context, well informed future application, careful consideration of cognitive science theories and psychosocial phenomenon. In this research, we have explored the role of Discussoo, an online platform for serious discussions (Anjum et al. 2021). In Discussoo the user can express their opinion in the discussion forum and at the same time, they review others' opinions.

For this paper, we have two hypotheses.

1. Discussoo can lead to change/shift in the participant's mental models (reflective learning).
2. Visualizing mental models during the discussion can lead to a better understanding among participants and help them to learn from each other

3. Methodology:

For this research, we conducted an experiment with university students. After receiving permission from the university, the researchers sought volunteer participants. More than 140 students were involved in the experiment. This experiment was conducted in three stages

1. **Pre-Survey:** For the first stages we have prepared a questionnaire with 8 open questions asking students about challenges faced by them during the covid time.
2. **Participation in Discussion conducted in Discussoo:** In the second stage, students were invited to Discussoo (a discussion forum for serious discussion) to participate in the discussion where they were asked to discuss about challenges faced by them during COVID19 time. Users can participate in the discussion by adding their comments and at the same time, they can respond and react to

others' comments. As the discussion is progressing, Discusoo is analyzing the discussion in real-time and visualizes the results as feedback within the platform.

3. **Post Survey:** After participating in the discussion, students were asked to fill out a survey with the same questionnaire with 8 open questions asking students about challenges faced by them during the covid time.

For the first hypothesis ("Discusoo can lead to change/shift in the participant's mental models (reflective learning)"), we cannot quantify the change in the mental model so we have used a survey with open questions where students can express their thoughts without any limitation. We assumed that there is evidence of change in the mental models of the participants who provide new answers to the same questions after they participated in the discussion at Discusoo. For this purpose, we prepared open questions about the topic of discussion (challenges of online learning during COVID). We have designed two questionnaires that students were asked to fill out before and after participating in the discussion posted at Discusoo.

The second hypothesis ("Visualizing mental models during the discussion can lead to a better understanding among participants and help them to learn from each other") is connected to the functionality that Discusoo provides and, by doing so, helps the participants to learn from the opinions of others. We used the "ladder of Inference" proposed by Peter Senge as components/steps that lead to reflection/learning. we have used the "ladder of Inference" proposed by Peter Senge as components/steps that lead to reflection/learning. The model was first put forward by organizational psychologist Chris Argyris and used by Peter Senge in "The Fifth Discipline: The Art and Practice of the Learning Organization." (Senge 2006). The Ladder of Inference describes the thinking process that we go through in order to decide and to take action based on the current situation/scenario, usually without realizing it. The important concepts for using the ladder of inference in order to encourage productive conversation and effective action are 1) keep on checking for inferences and be aware of your reasoning steps; 2) keep on exploring information that challenges your assumptions/beliefs, and 3) be aware of how our actions become information that is used by others to make inferences. The thinking stages can be seen as rungs on a ladder and are shown in Figure 5.2. By using the Ladder of Inference, you can learn to get back to the facts and use your beliefs and experiences to positive effect, rather than allowing them to narrow your field of judgment. Following this step-

by-step reasoning can lead to better results, based on reality, so avoid unnecessary mistakes and conflict.

We suggest that the use of Discussoo could assist in **'observing data'**, **'selecting data'**, **'adding meanings to the data'**, **'making assumptions'**, and **'coming up to conclusions'**. For each of these steps, we assigned several statements in the 'post' questionnaire. The participants should evaluate these statements based on the Likert scale (from strongly disagree to strongly agree') as shown in Figure 5.3. Therefore, when you will be analyzing the data accordingly. e.g., "if most of the participants rated statements 1 and 2 as 'strongly agree' which means that Discussoo can make information more accessible and eased the selection process".

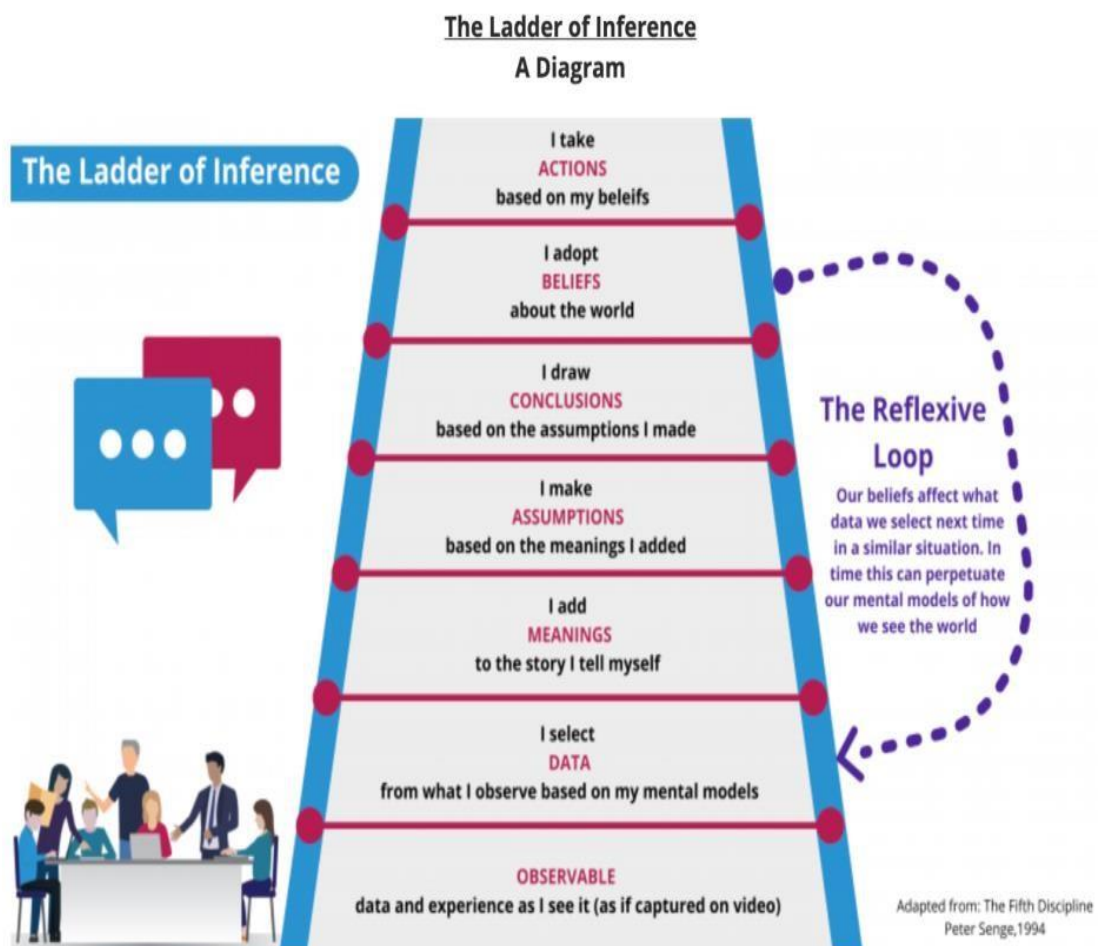


Figure 5.2. The Ladder of Inference
(Adopted from the Fifth Discipline by Peter Senge, 1994)

4. Case Study:

Discussoo was tested with students where they were asked to participate in a discussion about Covid challenges. Here is the discussion title:

“The Covid-19 pandemic brought extraordinary disruption to the education landscape with the campuses closing everywhere almost overnight. As a student how have you adjusted to life as an online student and what challenges have you faced?”

- *What role do you think that universities and colleges can play in finding solutions to overcoming the COVID-19 crisis?*
- *What should be the priority for universities? Should universities change the entire format? Should it be distant learning as the main course of the presentation of material?*
- *Should we transition to a new format? Should we go back to what we already had?”*

The Ladder of Inference



Figure 5.3. Ladder of Inference and Case Study questions

183 students participated in the discussion. Students were asked to respond to two questionnaires before and after participating in the discussion. In these questionnaires, students were asked open questions about challenges faced during Covid time.

5. Data Analysis

Inferential statistics are used to explore data for differences, relationships, and correlations in order to offer answers to research questions or hypotheses. In general, the kinds of inferential statistics that are utilized in the analysis are determined by the nature of the variables that are being analyzed. The chi-square test is the most fundamental inferential statistics test that is used (Waller et al. 2013) to assess the differences between categorical variables within the same population when analyzing cross-tabulations of survey data (Rolke & Gongora 2021). The chi-square statistic is employed when the variable is measured at the nominal level, also known as the category level. Each category is mutually exclusive from the others when working with nominal data. This information may be thought of as groups, with each piece of data belonging to just one of them. This statistic uses a percentage comparison to evaluate whether or not they are statistically significant. The proportions seen (data gathered) are compared to what they would be if there were no difference between the groups; this is the same as the null hypothesis (Gray et al. 2017).

The chi-square test of independence requires a number of assumptions to be satisfied in order for it to be conducted successfully i.e., a) The variables must be of the categorical kind, b) The sample must be drawn at random from the whole population so that every member of the population has an equal chance of being chosen (Bulinski et al. 2012), c) There can only be one instance of each observation in the contingency table, and d) All anticipated values should have a minimum of five points (Dodge, 2008). When looking up a crucial value on a chi-square table, the degrees of freedom are taken into consideration. The chi-square test of independence may be used to assess if two or more categorical variables are related or independent. Under the alternative hypothesis, the category variables may be linked to one another in some way. For the goal of making the research as simple as feasible, two-way chi-square tests of independence were utilized in this study.

6. Data cleaning and pre-processing

Before starting with the analysis, the data was extensively reviewed to ensure that each answer provided by each participant was authentic. Answers that fell outside of a preset range or conceptual framework (e.g., those who didn't respond to a question either presurvey or post-survey) were discarded. Missing data, including the sample frame, that can be quickly filled in from other portions of the same record has been restored to its original condition. Following a comprehensive examination by the researcher, an imputed value was substituted for a failed edit if the researcher was unable to contact a respondent. It was required to delete any names or emails to maintain anonymity. The researcher maintained and kept track of clear responses and accurate identities, as well as their right email addresses. Before and after the research, the total number of records for each session was kept track of and statistically evaluated. The word/text analysis was carried out using the NVIVO application (NVivo qualitative data analysis software; QSR International Pty Ltd. Version 12, 2018).

7. Results and Discussion:

In the present study, the responses added by respondents in before and after surveys were compared to one another. E.g., in the first question of the survey we asked: "What are the first three keywords that come to mind when you think of online learning during COVID19?" In response to this, 60 members (48.4 %) amended their statements, while the replies of three participants were deemed NA because their comments were only recorded either pre-survey, or only for post-survey, or not recorded at all for this particular question (Table 5.1 along with Figure 5.4). In this study, the chi-square χ^2 test of independence was used to test the null hypothesis that the frequency within cells is what would be expected, and it is well distributed equally across all levels of the relevant component. A chi-square test indicated that there is sufficient evidence to reject the null hypothesis as a consequence of this finding. A Chi-Square result suggested that the observed distribution differed from the predicted distribution (Figure 2) and that there was a close association between both categorical variables: (2, N = 248) $\chi^2 = 106.653$, $P < 0.001$. In the case of the first question, less than 50% of change was observed as most of the students were using the same keywords even after participating in the discussion so we can say that responses have not changed significantly.

Table 5.1. Results of Questions 1 (Pre and Post Survey: Question 1)

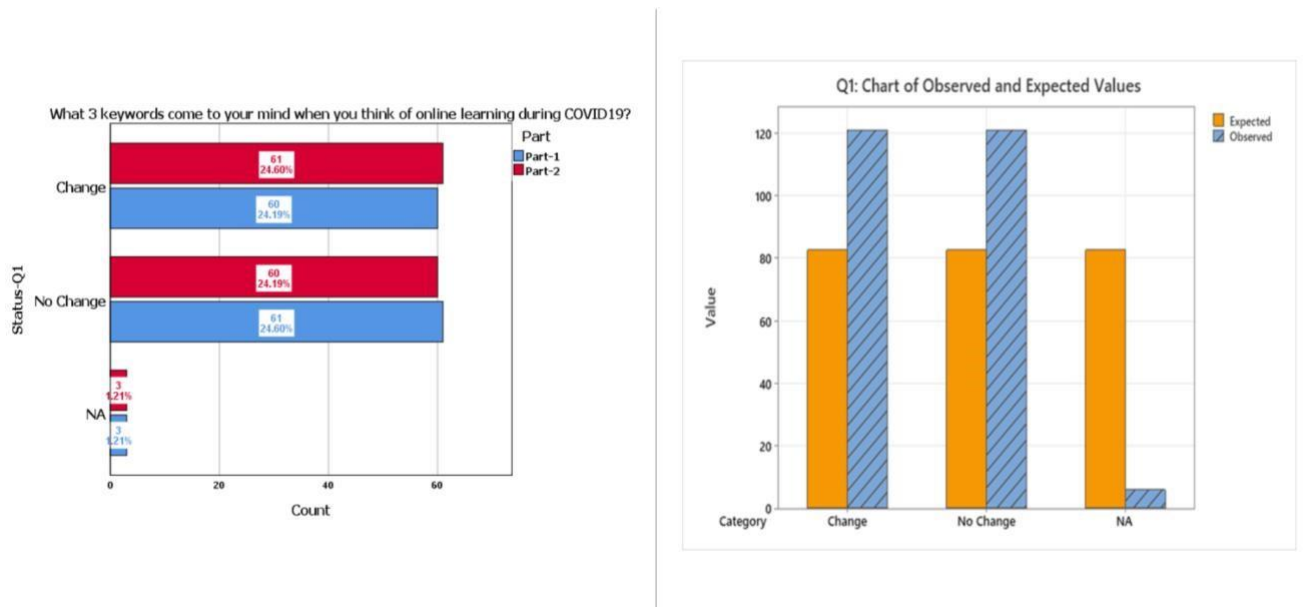


Figure 5.4. Results of Questions 1 (Pre and Post Survey)

Observed and Expected Counts

| Category | Observed | Test Proportion | Expected | Contribution to Chi-Square |
|-----------|----------|-----------------|----------|----------------------------|
| Change | 121 | 0.333333 | 82.6667 | 17.7755 |
| NA | 6 | 0.333333 | 82.6667 | 71.1022 |
| No Change | 121 | 0.333333 | 82.6667 | 17.7755 |

Chi-Square Test

| N | N* | DF | Chi-Sq | P-Value |
|-----|----|----|---------|---------|
| 248 | 0 | 2 | 106.653 | <0.0001 |

| Q1: What 3 keywords come to your mind when you think of online learning during COVID19? | | | | |
|---|---------------|--------|--------|--------|
| Status-Q1 | Count | Part-1 | Part-2 | Total |
| Change | Count | 60 | 61 | 121 |
| | % Within Part | 48.4% | 49.2% | 48.8% |
| No Change | Count | 61 | 60 | 121 |
| | % Within Part | 49.2% | 48.4% | 48.8% |
| NA | Count | 3 | 3 | 6 |
| | % Within Part | 2.4% | 2.4% | 2.4% |
| Total | Count | 124 | 124 | 248 |
| | % Within Part | 100.0% | 100.0% | 100.0% |

In the second question (What are the challenges that the students experienced the most in their learning during COVID time?) figure shows the change in the responses. Again, pre-and post-survey comments were compared Three responses were judged NA because their comments were only recorded either for pre-survey, or only for post-survey, or not recorded at all for this particular question. The result for

question number 2 is presented in Table 5.2 along with Figure 5.5. It was hypothesized that the frequency inside cells is what would be expected to be well distributed across all levels of the relevant component. If the third response (NA) is omitted from the analysis, it is clear that participants' answers before (59.68%) and after the training session (37.8 %) have changed significantly. Unlike question number where participants were just asking for very specific information (3 keywords about challenges during covid) in this question, participants were openly discussing challenges that they have experienced the most in their learning during COVID time. Most of the participants have either changed their response after participating in the discussion or they have elaborated further on their response.

Table 5.2. Results of Questions 2 (Pre and Post Survey)

Observed and Expected Counts

| Category | Observed | Test Proportion | Expected | Contribution to Chi-Square |
|-----------|----------|-----------------|----------|----------------------------|
| Change | 147 | 0.333333 | 82 | 51.5244 |
| No Change | 95 | 0.333333 | 82 | 2.0610 |
| NA | 4 | 0.333333 | 82 | 74.1951 |

Chi-Square Test

| N | N* | DF | Chi-Sq | P-Value |
|-----|----|----|---------|---------|
| 246 | 2 | 2 | 127.780 | 0.000 |

| Q2: What are the challenges that the students experienced the most in their learning during COVID time? | | | | |
|---|---------------|--------|--------|--------|
| Status-Q2 | Count | Part-1 | Part-2 | Total |
| Missing | Count | 1 | 1 | 2 |
| | % within Part | 0.8% | 0.8% | 0.8% |
| Change | Count | 73 | 74 | 147 |
| | % within Part | 58.9% | 59.7% | 59.3% |
| No Change | Count | 48 | 47 | 95] |
| | % within Part | 38.7% | 37.9% | 38.3% |
| NA | Count | 2 | 2 | 4 |
| | % within Part | 1.6% | 1.6% | 1.6% |
| Total | Count | 124 | 124 | 248 |
| | % within Part | 100.0% | 100.0% | 100.0% |

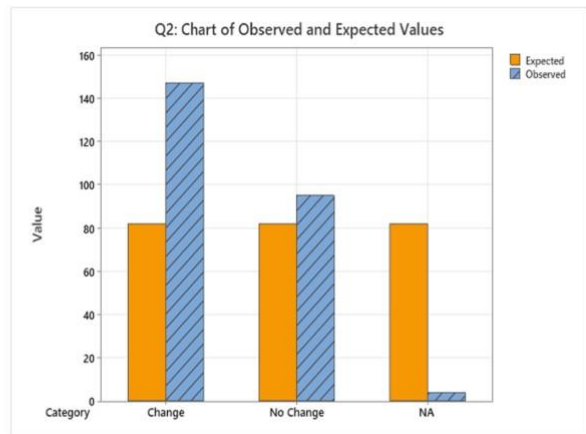
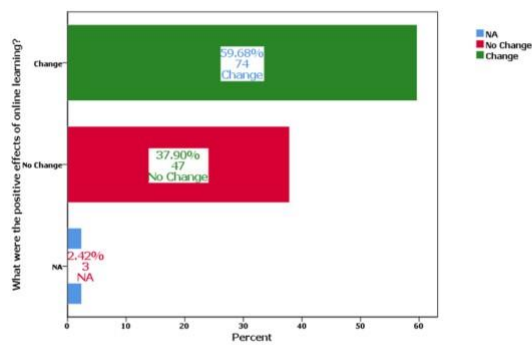


Figure 5.5. Comparison of Questions 2 (Pre and Post-Survey)

In the third question, we asked students “What were the positive effects of online learning?” Again, pre-and post-survey comments were compared. Table 5.3 along with Figure 5.6 shows the results of question number 3. It was hypothesized that the frequency inside cells is what would be expected to be well distributed across all levels of the relevant component. It can be clearly seen in the results that 59.68% change is observed in participants' answers.

Table 5.3. Results of Questions 3 (Pre and Post Survey)

Observed and Expected Counts

| Category | Observed | Test Proportion | Expected | Contribution to Chi-Square |
|-----------|----------|-----------------|----------|----------------------------|
| Change | 145 | 0.333333 | 82.6667 | 47.0013 |
| No Change | 97 | 0.333333 | 82.6667 | 2.4852 |
| NA | 6 | 0.333333 | 82.6667 | 71.1022 |

Chi-Square Test

| N | N* | DF | Chi-Sq | P-Value |
|-----|----|----|---------|---------|
| 248 | 0 | 2 | 120.589 | 0.000 |

| Q3: What were the positive effects of online learning? | | | | |
|--|---------------|--------|--------|--------|
| Status-Q3 | Count | Part-1 | Part-2 | Total |
| Missing | Count | 1 | 0 | 1 |
| | % within Part | 0.8% | 0.0% | 0.4% |
| Change | Count | 72 | 73 | 145 |
| | % within Part | 58.1% | 58.9% | 58.5% |
| No Change | Count | 48 | 48 | 96 |
| | % within Part | 38.7% | 38.7% | 38.7% |
| NA | Count | 3 | 3 | 6 |
| | % within Part | 2.4% | 2.4% | 2.4% |
| Total | Count | 124 | 124 | 248 |
| | % within Part | 100.0% | 100.0% | 100.0% |

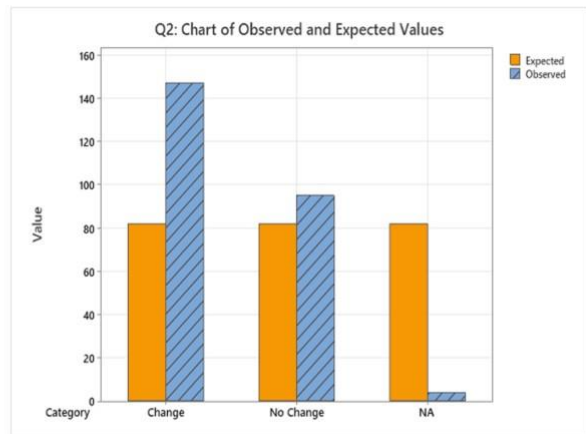
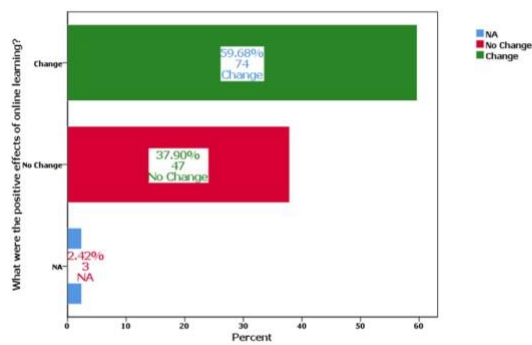


Figure 5.6. Comparison of Questions 3 (Pre and Post Survey)

In the fourth question, we asked students “What difficulties have you faced using online learning tools (Zoom, Microsoft Teams, etc.)?” and the result shows the change in the responses. Table 5.4 along with Figure 5.7 represents the result and it is clear that 51.62% change is observed in participants' answers.

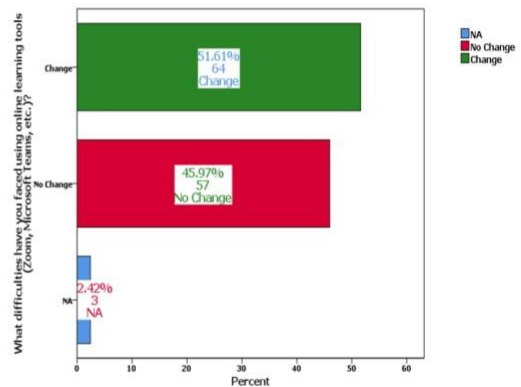
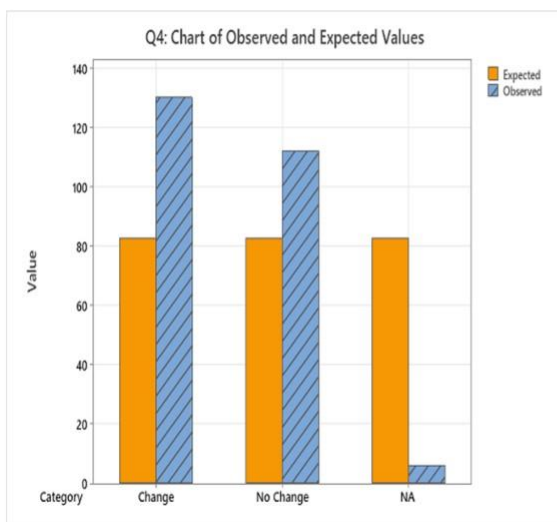


Figure 5.7. Comparison of Questions 4 (Pre and Post Survey)

Table 5.4. Results of Questions 4 (Pre and Post Survey)

Observed and Expected Counts

| Category | Observed | Test Proportion | Expected | Contribution to Chi-Square |
|-----------|----------|-----------------|----------|----------------------------|
| Change | 130 | 0.333333 | 82.6667 | 27.1022 |
| No Change | 112 | 0.333333 | 82.6667 | 10.4086 |
| NA | 6 | 0.333333 | 82.6667 | 71.1022 |

Chi-Square Test

| N | N* | DF | Chi-Sq | P-Value |
|-----|----|----|---------|---------|
| 248 | 0 | 2 | 108.613 | 0.000 |

| Q4: What difficulties have you faced using online learning tools (Zoom, Microsoft Teams, etc.)? | | | | |
|---|---------------|--------|--------|--------|
| Status-Q 4 | Count | Part-1 | Part-2 | Total |
| Change | Count | 65 | 65 | 130 |
| | % within Part | 52.4% | 52.4% | 52.4% |
| No Change | Count | 56 | 56 | 112 |
| | % within Part | 45.2% | 45.2% | 45.2% |
| NA | Count | 3 | 3 | 6 |
| | % within Part | 2.4% | 2.4% | 2.4% |
| Total | Count | 124 | 124 | 248 |
| | % within Part | 100.0% | 100.0% | 100.0% |

In the fifth question, we asked students about “what were the problems that students faced in group work during online learning” and the results show the change in the responses. From Table 5.5 along with Figure 5.8 it is clear that a 51.62% change is observed in participants' answers, hence we can say that responses have changed significantly.

Table 5.5. Results of Questions 5 (Pre and Post Survey)

Observed and Expected Counts

| Category | Observed | Test Proportion | Expected | Contribution to Chi-Square |
|-----------|----------|-----------------|----------|----------------------------|
| Change | 162 | 0.333333 | 82.6667 | 76.1344 |
| No Change | 78 | 0.333333 | 82.6667 | 0.2634 |
| NA | 8 | 0.333333 | 82.6667 | 67.4409 |

Chi-Square Test

| N | N* | DF | Chi-Sq | P-Value |
|-----|----|----|---------|---------|
| 248 | 0 | 2 | 143.839 | 0.000 |

| Q5: What were the problems that students faced in group work during online learning? | | | | |
|--|---------------|--------|--------|--------|
| Status-Q5 | Count | Part-1 | Part-2 | Total |
| Change | Count | 81 | 81 | 162 |
| | % within Part | 65.3% | 65.3% | 65.3% |
| No Change | Count | 39 | 39 | 78 |
| | % within Part | 31.5% | 31.5% | 31.5% |
| NA | Count | 4 | 4 | 8 |
| | % within Part | 3.2% | 3.2% | 3.2% |
| Total | Count | 124 | 124 | 248 |
| | % within Part | 100.0% | 100.0% | 100.0% |

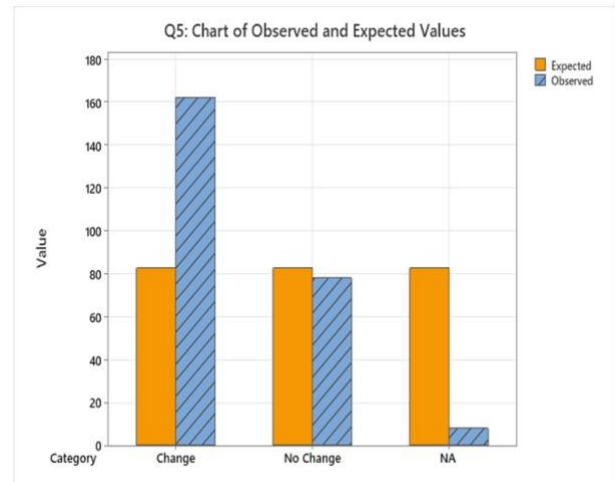
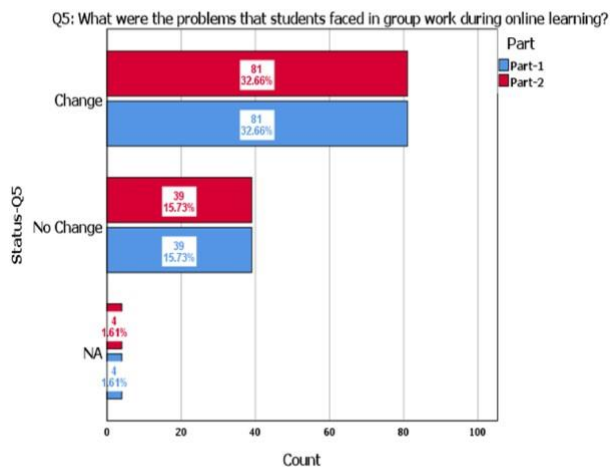


Figure 5.8. Comparison of Questions 5 (Pre and Post Survey)

In the sixth question, students are asked “What could the university have done better so that the students didn't face these challenges?” Table 5.6 along with Figure 5.9 present the results and it is clear that a 61% change is observed in participants' answers, hence, again, we can say that responses have changed significantly.

Table 5.6. Results of Questions 6 (Pre and Post Survey)

Observed and Expected Counts

| Category | Observed | Test Proportion | Expected | Contribution to Chi-Square |
|-----------|----------|-----------------|----------|----------------------------|
| Change | 152 | 0.333333 | 82.6667 | 58.1505 |
| NA | 8 | 0.333333 | 82.6667 | 67.4409 |
| No Change | 88 | 0.333333 | 82.6667 | 0.3441 |

Chi-Square Test

| N | N* | DF | Chi-Sq | P-Value |
|-----|----|----|---------|---------|
| 248 | 0 | 2 | 125.935 | 0.000 |

| Q6: What could the university have done better so that the students didn't face these challenges? | | | | |
|---|---------------|--------|--------|--------|
| Status-Q 6 | Count | Part-1 | Part-2 | Total |
| Change | Count | 76 | 76 | 152 |
| | % within Part | 61.3% | 61.3% | 61.3% |
| No Change | Count | 44 | 44 | 88 |
| | % within Part | 35.5% | 35.5% | 35.5% |
| NA | Count | 4 | 4 | 8 |
| | % within Part | 3.2% | 3.2% | 3.2% |
| Total | Count | 124 | 124 | 248 |
| | % within Part | 100.0% | 100.0% | 100.0% |

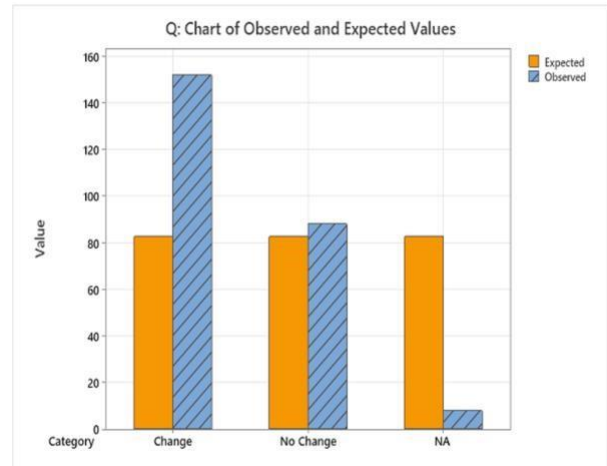
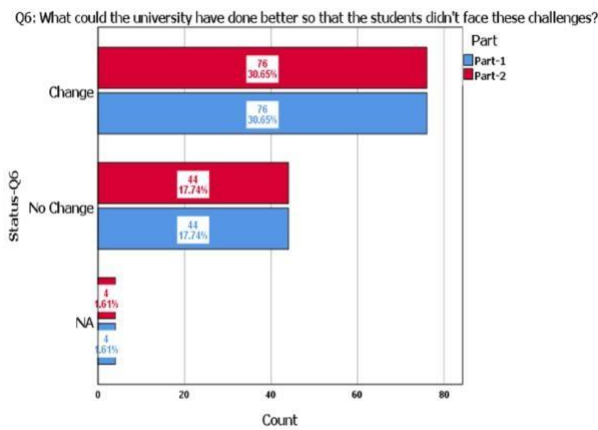


Figure 5.9. Comparison of Questions 6 (Pre and Post Survey)

In the seventh question, students were asked “What should be the priority for universities?” Four responses were judged NA because their comments were only recorded either pre-survey, or only for post-survey, or not added at all. It was hypothesized that the frequency inside cells is what would be expected to be well distributed across all levels of the relevant component. 58% change is observed in the responses which is seen in Table 5.7 along with Figure 5.10.

Table 5.7. Results of Questions 7 (Pre and Post Survey)

Observed and Expected Counts

| Category | Observed | Test Proportion | Expected | Contribution to Chi-Square |
|-----------|----------|-----------------|----------|----------------------------|
| Change | 140 | 0.333333 | 82.6667 | 39.7634 |
| No Change | 98 | 0.333333 | 82.6667 | 2.8441 |
| NA | 10 | 0.333333 | 82.6667 | 63.8763 |

Chi-Square Test

| N | N* | DF | Chi-Sq | P-Value |
|-----|----|----|---------|---------|
| 248 | 0 | 2 | 106.484 | 0.000 |

| Q7: What should be the priority for universities? | | | | |
|---|---------------|--------|--------|--------|
| Status-Q 7 | Count | Part-1 | Part-2 | Total |
| Change | Count | 70 | 70 | 140 |
| | % within Part | 56.5% | 56.5% | 56.5% |
| No Change | Count | 49 | 49 | 98 |
| | % within Part | 39.5% | 39.5% | 39.5% |
| NA | Count | 5 | 5 | 10 |
| | % within Part | 4.0% | 4.0% | 4.0% |
| Total | Count | 124 | 124 | 248 |
| | % within Part | 100.0% | 100.0% | 100.0% |

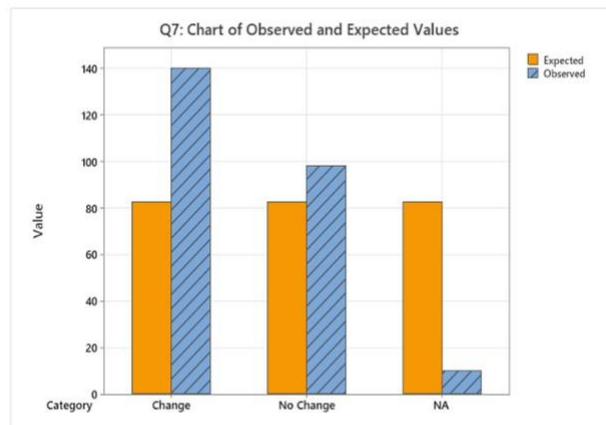
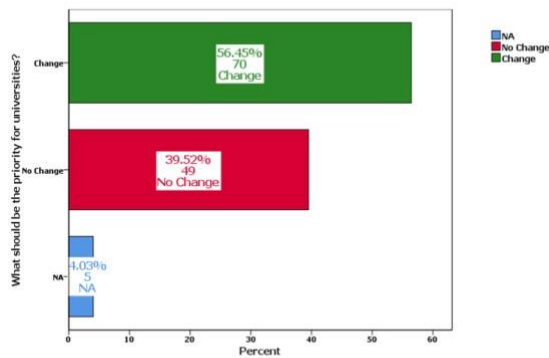


Figure 5.10. Comparison of Questions 7 (Pre- and Post-Survey)

In the last question, students were asked “Should universities transition to a new format or should they go back to what was before?” The figure shows a 56.4% change in the responses which is presented in Table 5.8 along with Figure 5.11.

Table 5.8. Results of Questions 8 (Pre- and Post-Survey)

Observed and Expected Counts

| Category | Observed | Test Proportion | Expected | Contribution to Chi-Square |
|-----------|----------|-----------------|----------|----------------------------|
| Change | 136 | 0.5 | 124 | 1.16129 |
| No Change | 112 | 0.5 | 124 | 1.16129 |

Chi-Square Test

| N | N* | DF | Chi-Sq | P-Value |
|-----|----|----|---------|---------|
| 248 | 0 | 1 | 2.32258 | 0.128 |

| Q8: Should universities transition to a new format or should they go back to what was before? | | | | |
|--|---------------|--------|--------|--------|
| Status-Q 8 | Count | Part-1 | Part-2 | Total |
| Change | Count | 68 | 68 | 136 |
| | % within Part | 54.8% | 54.8% | 54.8% |
| No Change | Count | 56 | 56 | 112 |
| | % within Part | 45.2% | 45.2% | 45.2% |
| Total | Count | 124 | 124 | 248 |
| | % within Part | 100.0% | 100.0% | 100.0% |

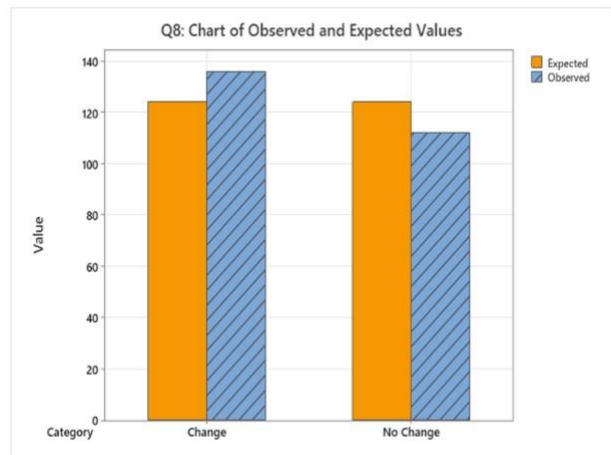
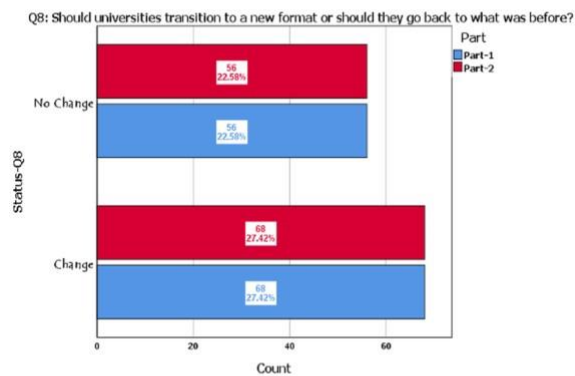


Figure 5.11. Comparison of Questions 8 (Pre- and Post-Survey)

Overall, in the pre-survey, the corpus has 7,841 total words and 1,722 unique word forms. Most frequent words in the corpus: students (148); learning (146); internet (106); time (86); issues (80) as shown in Figure 5.12. The post-survey corpus has 11,535 total words and 2,179 unique word forms. Most frequent words in the corpus: learning (207); students (203); online (140); time (107); internet (106) as shown in Figure 5.13. It is important to note that result of the pre- and post-survey are different and more than 50% of changes is observed hence proving our first hypothesis that “Discussoo can lead to change/shift in the participant's mental models (reflective learning)”.

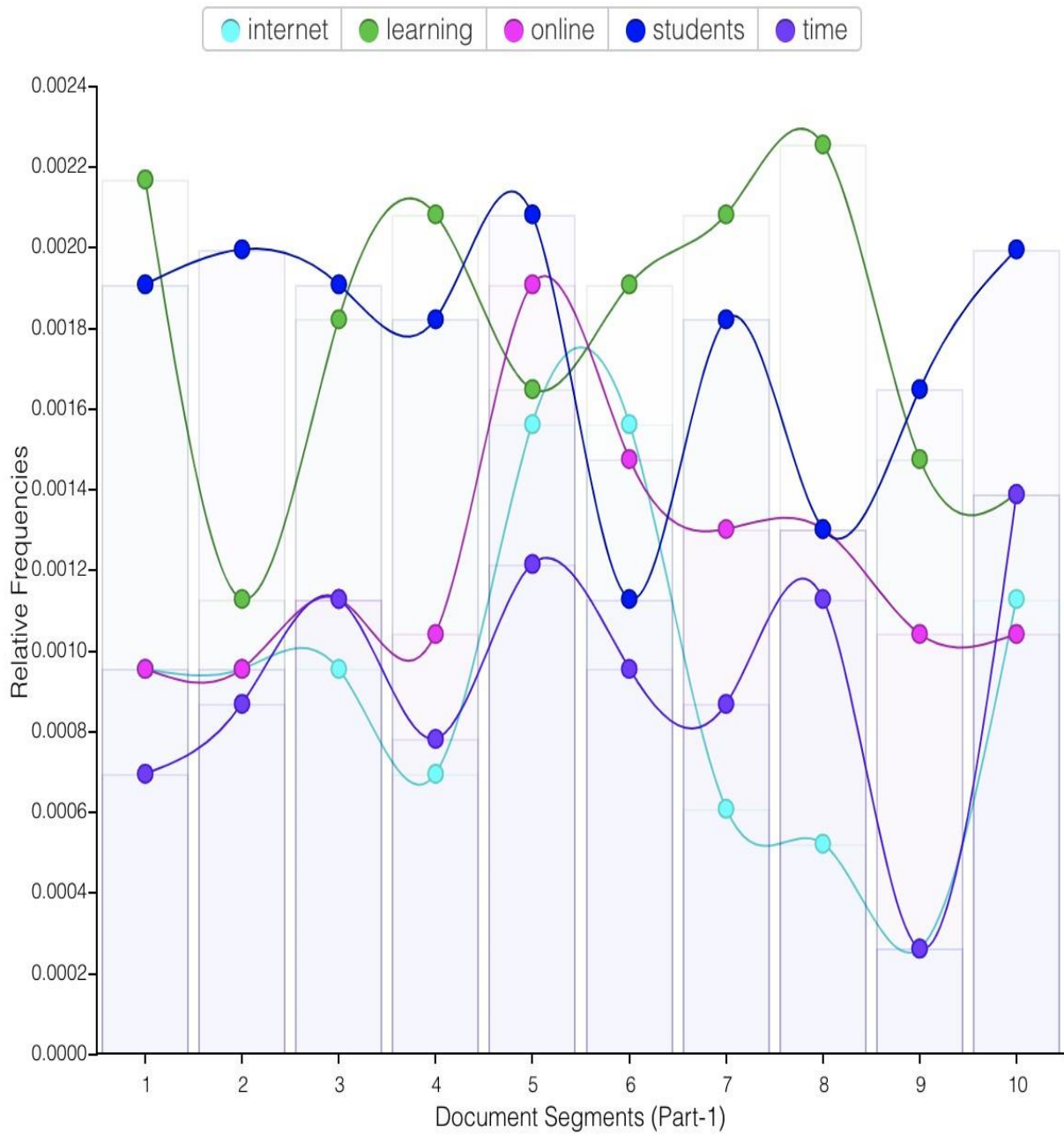


Figure 5.12. Representing line graph of relative frequencies in Pre survey responses

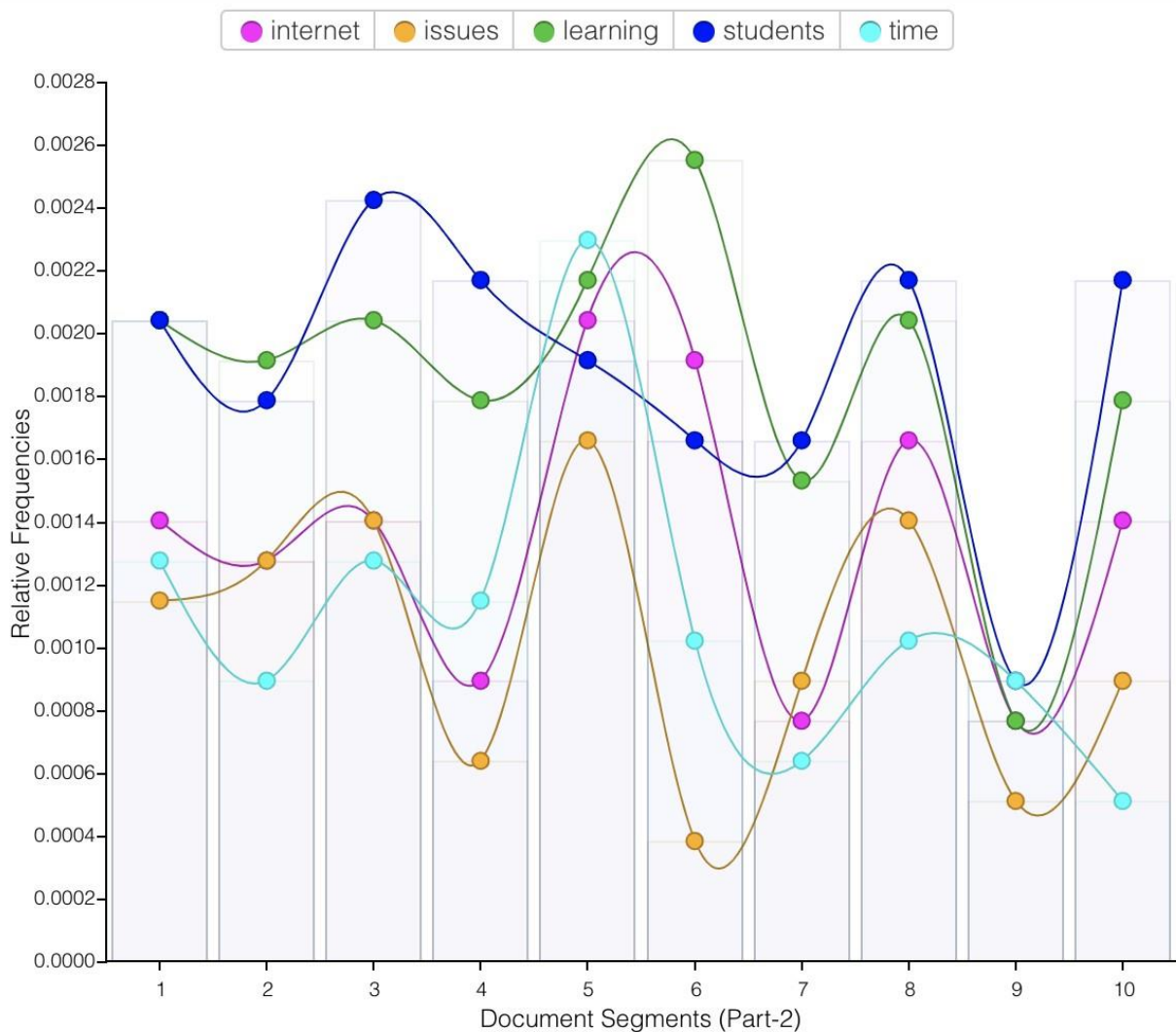


Figure 5.13. Representing line graph of relative frequencies in Post survey responses

The second hypothesis (“Visualizing mental models during the discussion can lead to a better understanding among participants and help them to learn from each other”) is connected to the functionality that Discussoo provides and, by doing so, helps the participants to learn from the opinions of others. We have used the 'ladder of Inference' proposed by Peter Senge as components/steps that lead to reflection/learning. We suggest that the use of Discussoo could assist in '**observing data**', '**selecting data**', '**adding meanings to the data**', '**making assumptions**', and '**coming up to conclusions**'.

For each of these steps, we assigned several statements in the 'post' questionnaire. The participants evaluate these statements based on the Likert scale (from strongly disagree to strongly agree') and the results are presented in Figure 5.14.

48% of students have selected “Agree”, 18% have selected “Agree”, 21% selected neutral, 5% of students selected ‘Disagree’ and 9% of students selected “strongly disagree”. Overall, 66% agreed hence proving our second hypothesis that “Visualizing mental models during the discussion can lead to a better understanding among participants and help them to learn from each other”.

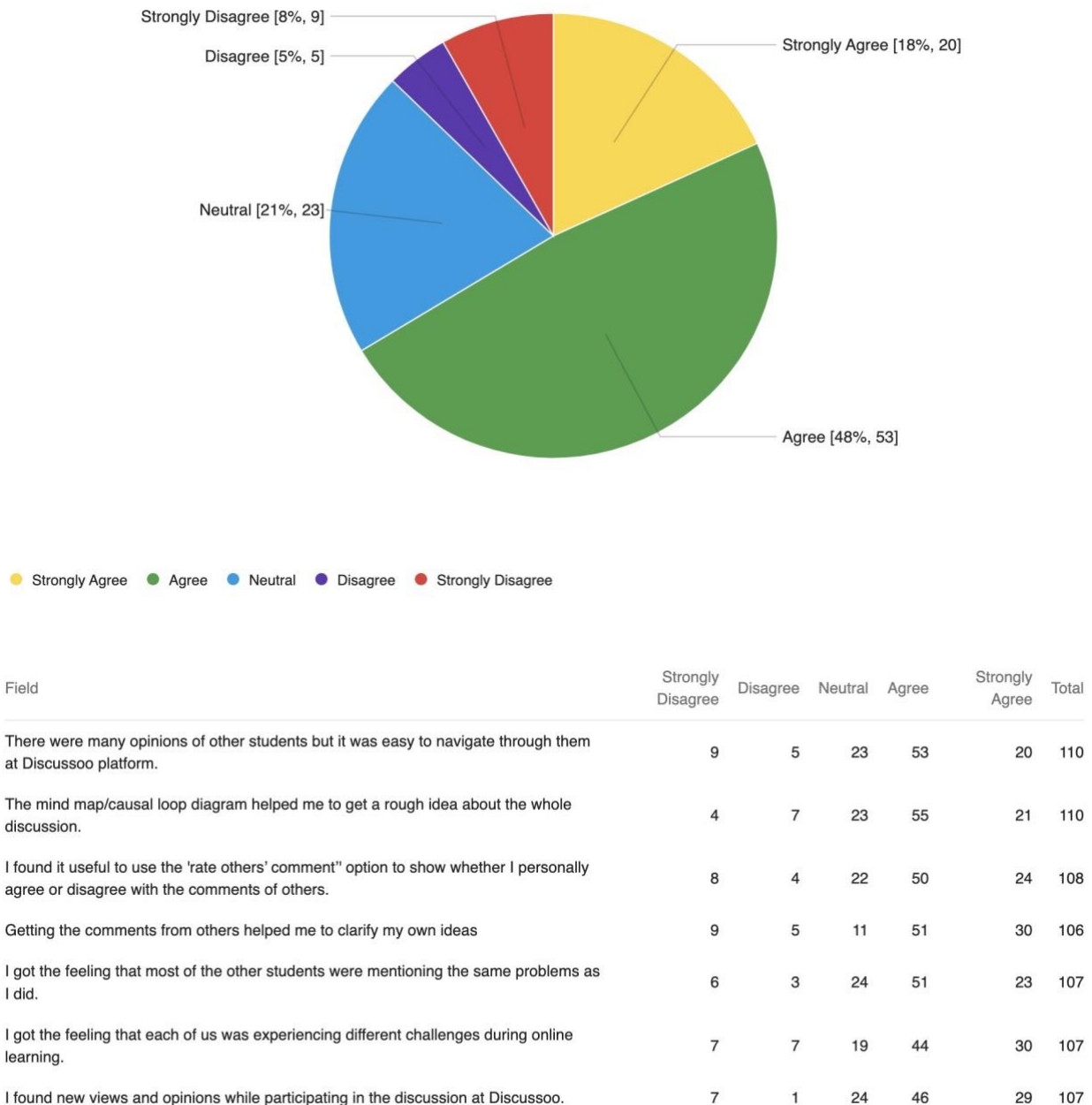


Figure 5.14. Results about “Discussoo can assist in 'observing data', 'selecting data', 'adding meanings to the data', 'making assumptions', and 'coming up to conclusions'”

| Field | Min | Max | Mean | Standard Deviation | Variance | Responses |
|--|------|------|------|--------------------|----------|-----------|
| There were many opinions of other students but it was easy to navigate through them at Discussoo platform. | 1.00 | 5.00 | 3.64 | 1.08 | 1.18 | 110 |
| The mind map/causal loop diagram helped me to get a rough idea about the whole discussion. | 1.00 | 5.00 | 3.75 | 0.96 | 0.92 | 110 |
| I found it useful to use the 'rate others' comment" option to show whether I personally agree or disagree with the comments of others. | 1.00 | 5.00 | 3.72 | 1.08 | 1.16 | 108 |
| Getting the comments from others helped me to clarify my own ideas | 1.00 | 5.00 | 3.83 | 1.14 | 1.31 | 106 |
| I got the feeling that most of the other students were mentioning the same problems as I did. | 1.00 | 5.00 | 3.77 | 1.00 | 1.00 | 107 |
| I got the feeling that each of us was experiencing different challenges during online learning. | 1.00 | 5.00 | 3.78 | 1.12 | 1.26 | 107 |
| I found new views and opinions while participating in the discussion at Discussoo. | 1.00 | 5.00 | 3.83 | 1.05 | 1.09 | 107 |

Figure 5.15. Results about “Discussoo can assist in '**observing data**', '**selecting data**', '**adding meanings to the data**', '**making assumptions**', and '**coming up to conclusions**'”

Changes in mental models give people a fresh perspective on the world, which benefits individuals and communities. The mental models shape the perceptions and actions individuals have of the world (Patton et al. 2019). As a result, people rely on these mental models to help them navigate the world, form sound judgments and find practical solutions to any issues that may arise (van Bruggen et al. 2019). Since mental models trigger our understanding of the cognitive processes, it is reasonable to suppose that they play a primarily facilitative role in the advancement of solving issues during the early stages. Experiencing alternative models produced by other participants seems to impact learning significantly. Changes in perception, thinking or ideas are difficult to measure (McNeil 2015). In this research, we have focused on identifying the cognitive changes by comparing the externalized representations of students' mental models.

We have used Discussoo as an interactive discussion forum where students are expressing their thoughts about the challenges faced by them during the COVID period and at the same time students can see what others are expressing. It is important for teachers and education institutes to use strategies that can help them to elicit/understand how students think. Teachers can use this collected knowledge to interpret and respond strategically to students thinking. There are several benefits of social interactions in online discussion forums but at the same time, very limited attention has been given to understanding the content/data of these interactions.

There are many reasons for this, e.g., it takes a lot of time to deal with a huge amount of data (Prinsloo & Slade 2017) and at the same time, there are very limited approaches available for analyzing and visualizing unstructured data on the go (Tawfik et al. 2019). The main purpose of this study is to identify changes in users' opinions through feedback introduced in the tool. Involving students in a discussion platform where they can add their opinion and at the same time can access others' opinions can lead to collaborative learning and knowledge construction (Kovanović et al. 2016). The changes in students' mental models can enhance the capacity for knowledge discovery. In Discusoo by using advanced data mining technologies we can provide feedback to students about their and others' opinion in the form of visualization. These visualizations can enhance the capacity for knowledge discovery.

By sharing a mental model, a person helps others to conceptualize a particular process or topic. Sharing knowledge is also a major part of the co-creation of a mental model in a socio-cultural environment where verbal and nonverbal communication is the key. Sharing the mental model completely or partially within a group is participatory modelling. In accordance with the conceptualization of (Maynard & Gilson 2014), it can be said that the participatory mental model is very useful for multi-stakeholder conservation, where all individual participants share their mental model partly or completely with each other to develop a mental model in a collective way. The conversation represents the collectively developed mental model to a degree to which a common conceptualization of an issue exists. As explained by Henly-Shepard, Gray & Cox (2015), the mental model is not shared completely in most of the time, whereas usually mental model is shared partly, where a partial structure of mental model sharing helps the receiver to update or refine his or her mental model partially with the new concept and knowledge.

The mutually shared and participatory mental model usually develops through multiple iterations of mutual discussion and conceptualization within a group where a similar representation of the issue is constructed. This collective construction of the mental model is a base of the shared understanding and joint action or movement in a socio-cultural environment. If any socio-cultural gap or language barrier presents within the mental model sharing, misinterpretation and misunderstanding can occur and, in that case, a mental model refining and updating process can be disrupted.

8. Conclusions

Conclusively Discusoo platform can allow the moderator to extract and analyze cognitive maps that provide relevant and actionable insights into questions about the structure and evolution of a mental model of a population or a group of people. This moderator can be a researcher, or representing a government agency, non-profit or private organization and can assist in extracting the mental model from a group of people discussing a particular topic. A system based on this framework will be able to provide valuable information to both users and moderators while interpreting the group's mental model in different ways. As a result, it can produce new and creative solutions to complex problems and controversial societal issues, or it can help to predict future consequences of a decision. This framework could be used in various settings and problem situations where the steering of collective mental models could improve the functioning, resilience and/or sustainability of a given system that includes social, environmental, or technical fields. It can also be used by the policy makers or any other organization that would benefit from a more direct, transparent and meaningful engagement of its stakeholders.

In theory, decision makers and managers could benefit greatly from employing the mental model framework to learn more about how individuals think about and, therefore, interact with their environment. Besides participants' attitudes, ambitions, and values connected with a specific asset, a developed mental model of cognition provides a detailed description of how interested parties understand complex systems and processes. What ideas stakeholders deem most important to a particular problem, how these conceptions are arranged intellectually, and how they interact dynamically may be gleaned from this image. People's understanding of a system, their expectations about how that system will react to initiatives and their willingness to act are all illuminated by this perspective. A system's complete knowledge may be improved, and central planning can be supported by comparing similarities and contrasts in comprehension throughout time and location. Increasing conceptual evidence from the disciplines of psychology and behavior suggests that humans do utilize mental models to sense and anticipate the universe surrounding them. Teachers may learn from the dynamics of mental models of their students whether they are progressing toward a deeper understanding of the systems analyzed, or whether the important concepts and elements are properly identified and interpreted.

Chapter 6: Conclusion

1. Development of an AI-based online, moderated tool for serious discussions

With the advent of social media and various online tools, there are more opportunities for meaningful and productive interaction with stakeholders, potentially enhancing if not substituting some parts of in-person engagement. However, some of the existing social media (Twitter, Facebook, etc.) has not been designed for serious discussions among stakeholders and, when used without care, can even be detrimental to productive engagement. We have built an online tool specifically designed to help engage stakeholders and improve their interaction in search of solutions to problems. Discusoo has been initially designed to support multi-scale participatory modelling but has been expanded to handle all sorts of stakeholder engagement while enriching the process with AI-generated content.

Users respond to or expand on other users' opinions and/or initiate new lines of discussion. The discussion chain is mined in real-time, using an ensemble of algorithms to extract opinions, keywords, and concepts, further analyzed in the form of clusters where clusters represent how different concepts are linked or related to each other. This information is transcribed into conceptual models as the discussion evolves. To provide feedback, the system presents users with dynamic visualizations of the collective mental model, which they can use as contextual information to refine and update their individual mental models. Feedback can also be introduced by targeted moderator comments to steer or "nudge" the discussion towards a desirable collective mental model, outcome, consensus, or agreement.

This framework can be used in a variety of settings and problem situations where the steering of collective mental models could improve the functioning, resilience and/or sustainability of a given (social, environmental, or technical) system, or used by policymakers or any other organization who would benefit from a more direct, transparent and meaningful engagement of its stakeholders.

2. Facilitating PM workshops using Discussoo

PM practitioners usually organize a series of workshops for the involved stakeholders to share their ideas and preferences and solicit input from them about the existing knowledge about the system and the decisions to be developed. These workshops are usually restricted in time and can accommodate only a limited number of participants. It would be hard to conduct a constructive discussion with too many stakeholders invited and to get all of them to join a workshop at a particular time in one place. One could refer to the existing online platforms to mimic some of the discussions usually occurring during workshops. However, they offer limited access to the information collected in the comments, making it hardly possible to process the comments and derive any knowledge from them. Moreover, existing platforms do not assume any place or role for facilitators or moderators of the discussion, who could guide the discussion or provide users with instant feedback. These considerations convinced us that instead of relying on existing platforms, we should develop a specialized online tool that can be deployed in any PM process.

This tool, Discussoo, provides a platform for stakeholders to share their opinions by submitting comments, while the recorded texts are immediately processed and information is extracted from available comments in an attempt to generate on the fly conceptual models of the systems discussed, which can be immediately fed back into the discussion for stakeholder checking and confirmation. Discussoo is a generic solution that aims to enable effective scalable discussions among stakeholders. Indeed, the moderation functionalities and the AI-powered features, both with smart management of different discussion threads, create a digital environment that encourages focused discussions and, eventually, decision making. The tool has not been designed to address specific topics or to work exclusively in a given application domain. It is rather understood as a generic asset. However, from the experience matured so far, we expect the adoption of the tool in fields characterized by a variety of stakeholders, such as sustainability and policy making.

3. Mapping Mental Models from an Online Discussions platform

Mental models are mental representations of reality. Usually, mental models are elicited with the guidance of an expert who collaborates with stakeholders to synthesize their key ideas. However, this expensive process is not affordable for many organizations. Thus, the development of computational systems for automatic mental model analysis could foster learning and a shared understanding of complex problems.

Discusoo platform is a smart real-time tool that can help understand and formalize mental models based on text taken from online discussions. It allows users to respond or elaborate on other users' opinions and/or initiate a new line of discussion. The extracted data from the discussion are analyzed using Artificial Intelligence (AI) and transcribed into semi-quantitative models – Conceptual models, and Networks Diagrams. To the best of our knowledge, there is no tool/system for supporting automatic mental map generation. Discusoo is one of the first platforms developed to facilitate effective and scalable discussions between stakeholders through presenting discussion-based mental models using AI techniques. It enables facilitators to understand, analyze and visualize mental models. It presents a structured and machine-processable representation of a discussion in an abstract way so that all key knowledge is summarized. Creating a visual representation of mental models requires at least three phases: elicitation, analysis, and representation. Most elicitation techniques in mental model elicitation rely heavily on how the participants' responses have been interpreted by the interviewer. It can be time consuming and costly, allowing biases to seep into responses at the end.

Discusoo can avoid any kind of biases to seep into the responses at the end. In the analysis phase combined or mixed methods can lead to an increase in complexity but in the case of Discusoo all the discussions are being analyzed in real time so it can save time. Unlike the other quantitative methods, it can capture information regarding emotions which is a very important factor in the case of mental models. Instead of using one technique for analyzing mental models, in Discusoo several techniques are deployed to deliver a comprehensive analysis of text data. There are several techniques for representing mental models but most of them are hard to understand for those stakeholders who are not expert in the field. In Discusoo the results are represented in intuitive and interactive visualizations, such as word clouds for concepts, sentiment

analysis and network diagrams, so that users can easily interpret the outcome of a discussion or group decision making.

The proposed platform for understanding and eliciting mental models from the group discussions can be useful as mental models can be used to develop relevant and actionable insights about different social, political, scientific and other questions.

4. Reconstructing mental models through a moderated framework for serious discussion

We have examined the cognitive change in mental models of students and consequently change in their opinion due to their participation in an online discussion forum. We had two hypotheses in this research. The first hypothesis is that “Discussoo (a platform for online discussions) can cause mental models to change and evolve”.

We tested this hypothesis by conducting an experiment with 165 students where they were asked about challenges, they faced during the COVID-19 period. Each student was first asked to fill out a survey where they had to answer eight open questions related to covid 19 challenges. After providing their answers, students were redirected to Discussoo, where they participated in the discussion about challenges, they faced during the COVID-19 period. After discussion, students filled out the same survey once again. There is evidence of change in the mental models of the participants who have provided new answers to the same questions after participating in the discussion at Discussoo. More than 60% of students have changed their answers. Our second hypothesis is that “visualizing mental models during the discussion can lead to a better understanding among participants and help them to learn from each other”.

This hypothesis is connected to the functionality that Discussoo provides and, by doing so, helps the participants to learn from the opinions of others. We used the "ladder of Inference" proposed by Peter Senge as components/steps that lead to reflection/learning. We suggest that the use of Discussoo could assist in 'observing data', 'selecting data', 'adding meanings to the data', 'making assumptions', and 'coming up to conclusions'. We assigned several statements in the 'after' questionnaire for each of these steps. The participants should evaluate these statements using the Likert scale (from strongly disagree to strongly agree). Most of the participants rated statements 1 and 2 as 'strongly agree, ' meaning that Discussoo made information more accessible and simplified the selection process. Overall understanding of

individual/group mental models in a discussion forum can improve knowledge and help to accommodate a plurality of values, perceptions, and beliefs among stakeholders, thereby increasing the chance of implementation success.

5. Research Contributions

The main contributions of this research are outlined below:

- Explore why mental models are important in user interaction and decision making.

Conduct literature review and identify ways to solicit and share mental models.

- Design and implement a user-friendly on-line platform - Discusoo.com - to support serious discussions, providing tools for soliciting comments, reactions, impressions, and offering moderation techniques to handle and improve the discussions.
- Define, identify and extract key elements from a discussion that are needed to formulate mental models - concepts, keywords, weights and relationships.
- Visualize mental models extracted from a discussion forum as conceptual or network diagrams.
- Identify how moderators can nudge the behavior of users in an online discussion by showing already extracted mental models.
- Explore if users reconstruct knowledge or change their mental models based on their interactions with visualizations of a mental model.

Overall, the outcome of this research is an online discussion framework that can capture representations of a group's mental model from an online web forum and translate these into conceptual models. Discusoo is not just another 'survey' or voting system that governmental agencies could use for citizen engagement. It aims at (1) extracting meaningful ideas from the citizens (not just binary answers) that could help the policymakers to see the actual concerns of people (and, therefore, better manage

risks and adjust policies), (2) creating a learning environment for the citizens so they could improve their understanding of the problem and get ownership of the solution (this, in turn, would help the policymakers at the stage of policy implementation), (3) avoiding cost-time-effort constraints that governmental agencies experience when they need to organize large-scale public consultations with stakeholders.

6. Why use Discussoo

- (1) Time/cost/effort: we make it more efficient from all these perspectives by automatically processing the public discussions and making commenting more engaging.
- (2) A feeling of being understood, with improved stakeholder ownership of the decisions made or policies developed.
- (3) Diffuse learning outcomes in the audience/users - not just extracting information from people but giving something in return.

7. Future Research

This study suggests several potential directions for future research.

- Firstly, we can do further refinement and generate a more precise mental model when more data becomes available. When coming up with a filtration strategy to clean concepts or key phrases, the more data, the merrier.
- In future research, we can compare an individual's mental model with the group model and analyze the evolution of mental models over time. We can also explore how users reconstruct knowledge and change their mental models based on their interactions with formal models.
- We can develop questionnaires, surveys to assist stakeholders in formulating their ideas in a way that could be more easily communicated and processed when delivering a GMM.
- A number of effective security mechanisms can be devised to protect users' mental models from malicious use.
- In the future multiple approaches can be considered for taking input from users. Instead of just taking user input in the form of text, voice and multimedia can also be used.



Appendix

Example 1

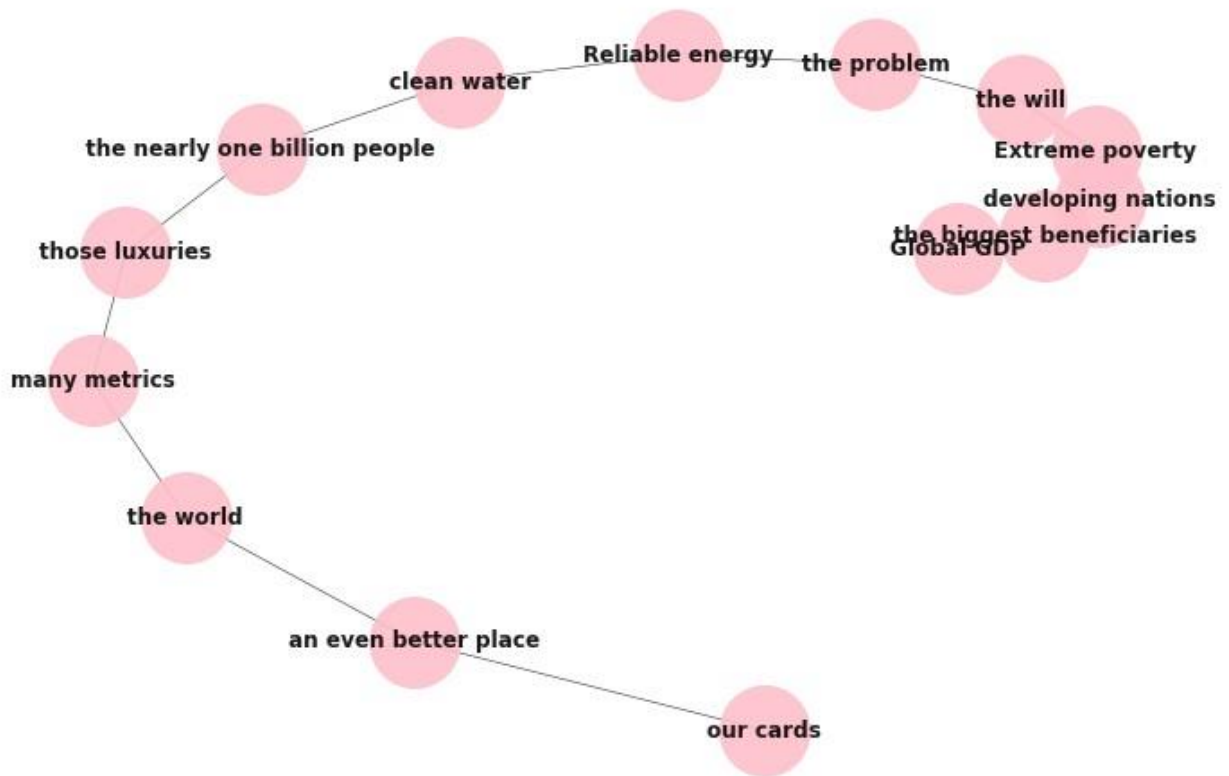
Topic Rank:

hopeless

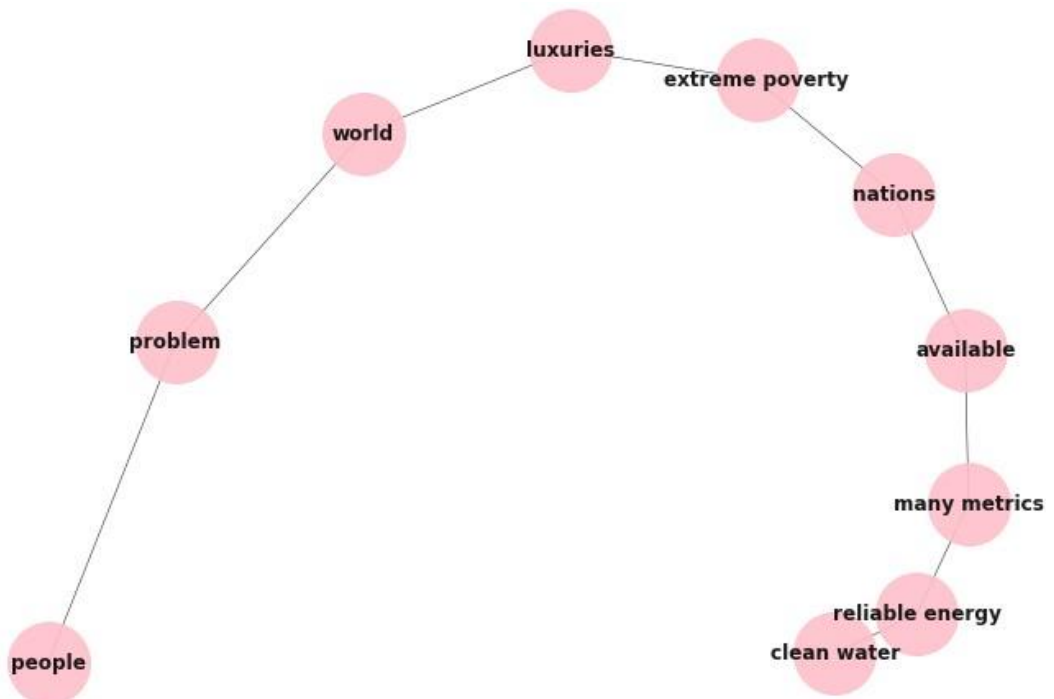
Text Rank:

hopeless

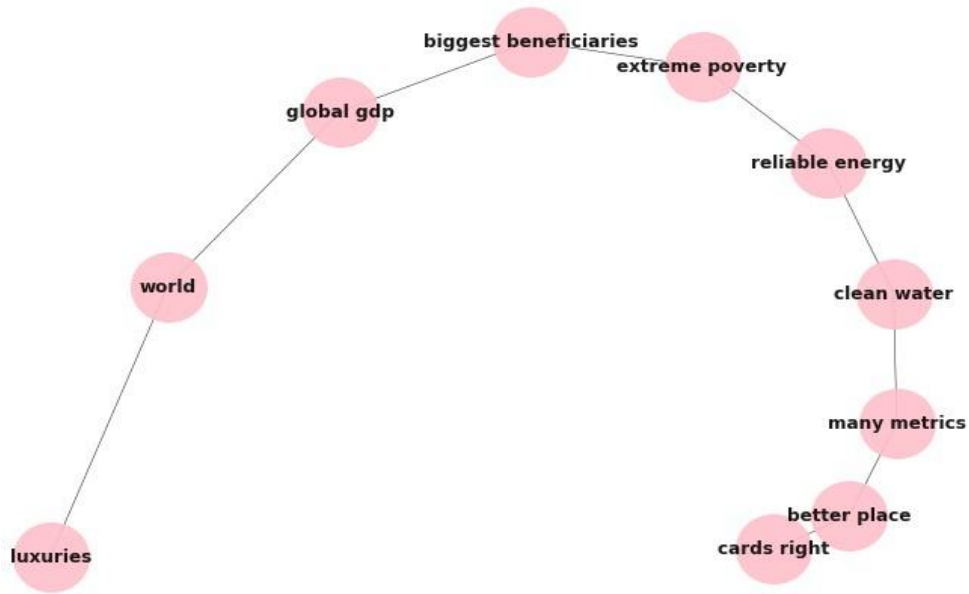
Example 2 TFIDF:



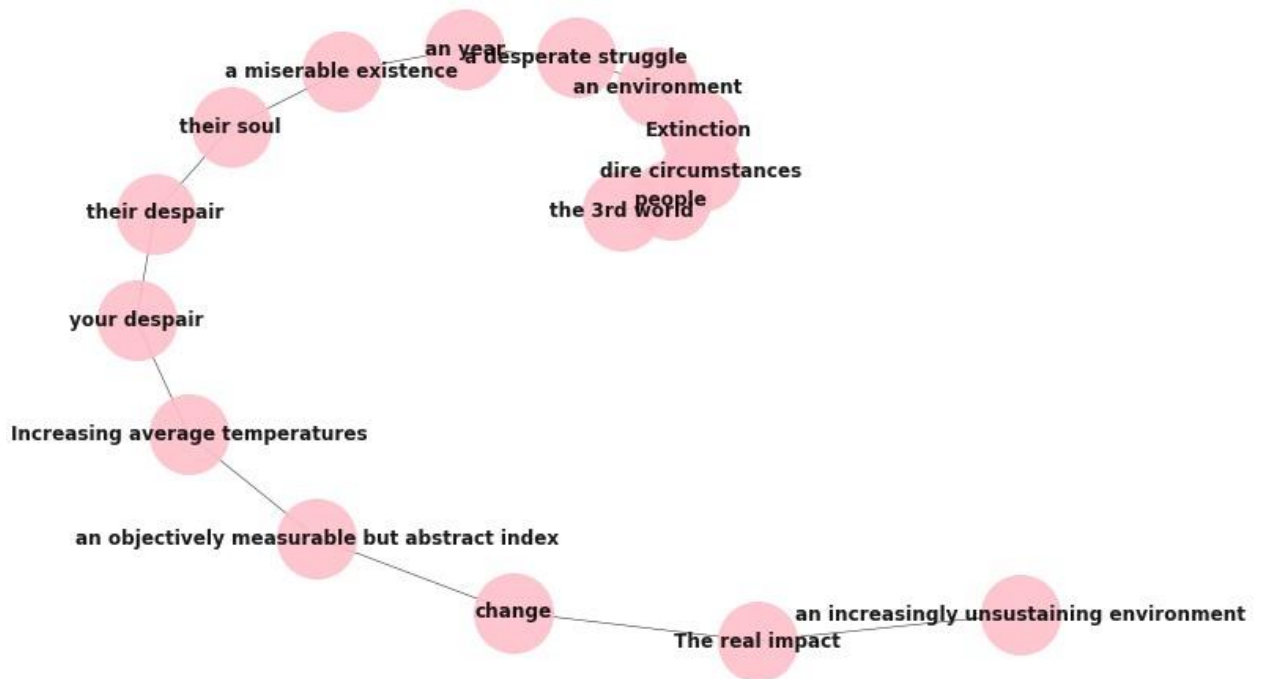
Topic Rank:



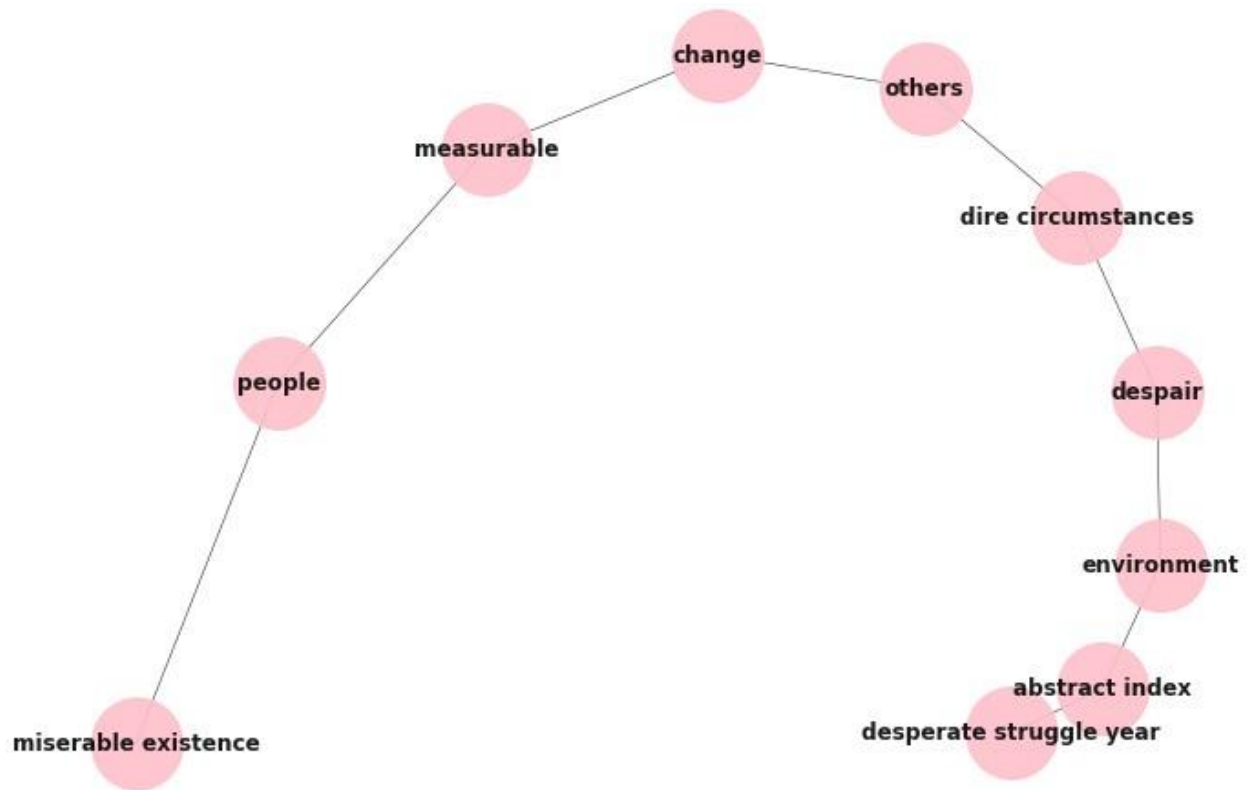
Text Rank:



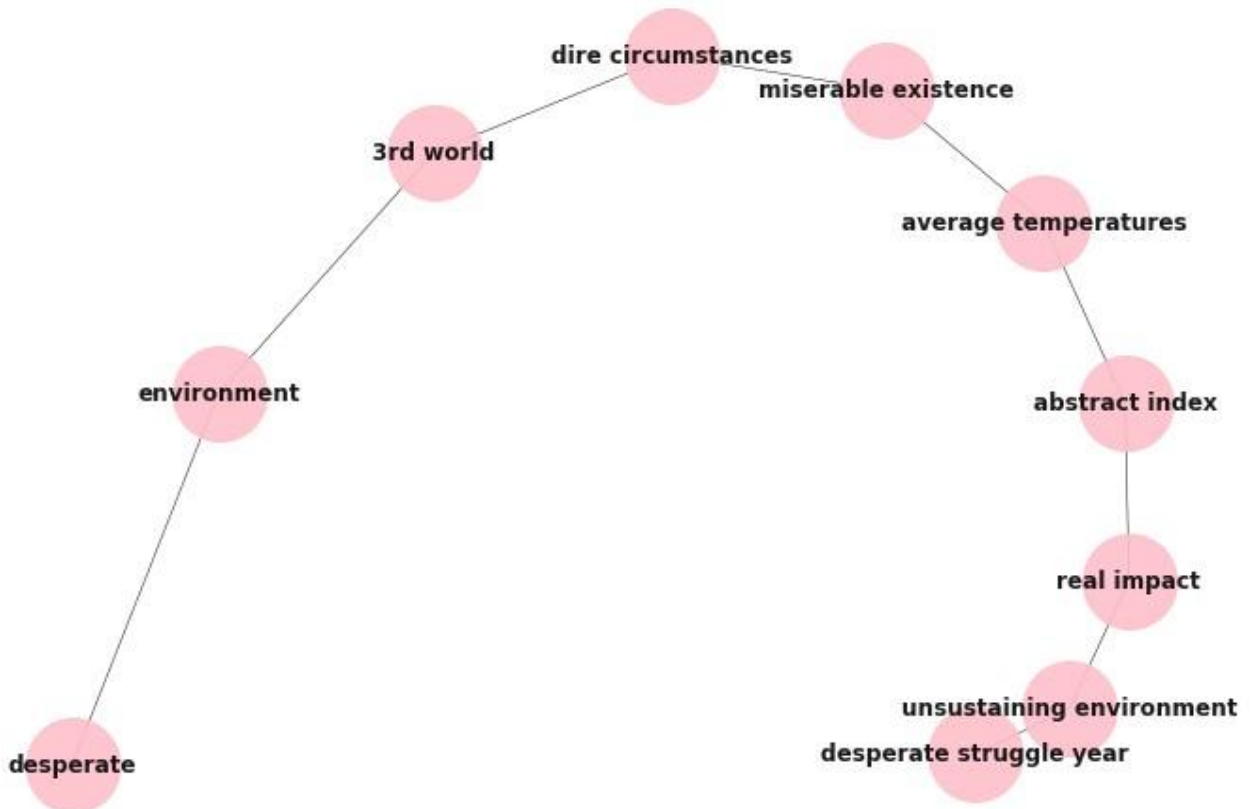
Example 3 TFIDF:



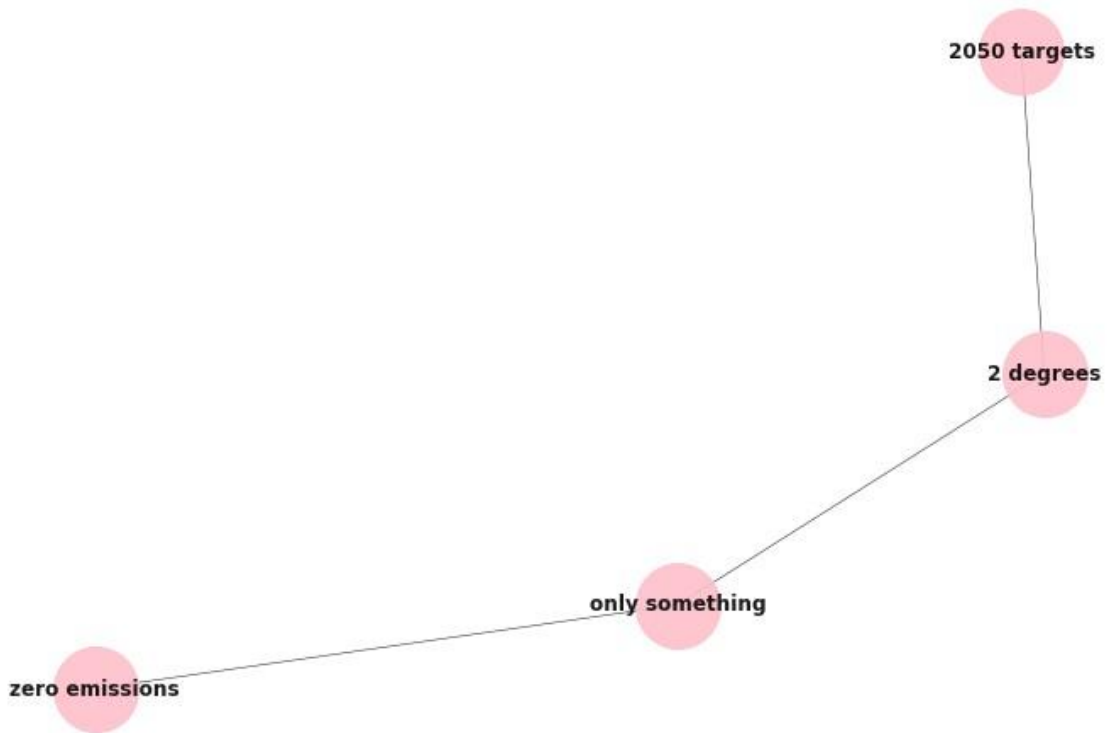
Topic Rank:



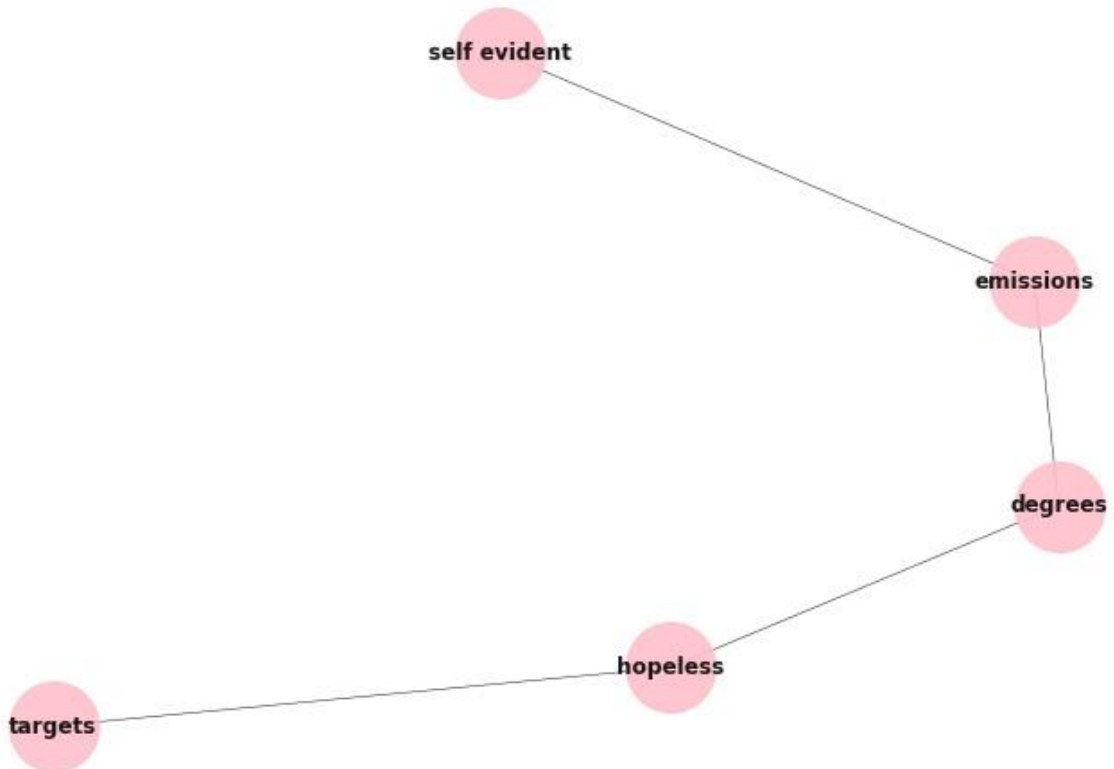
Text Rank:



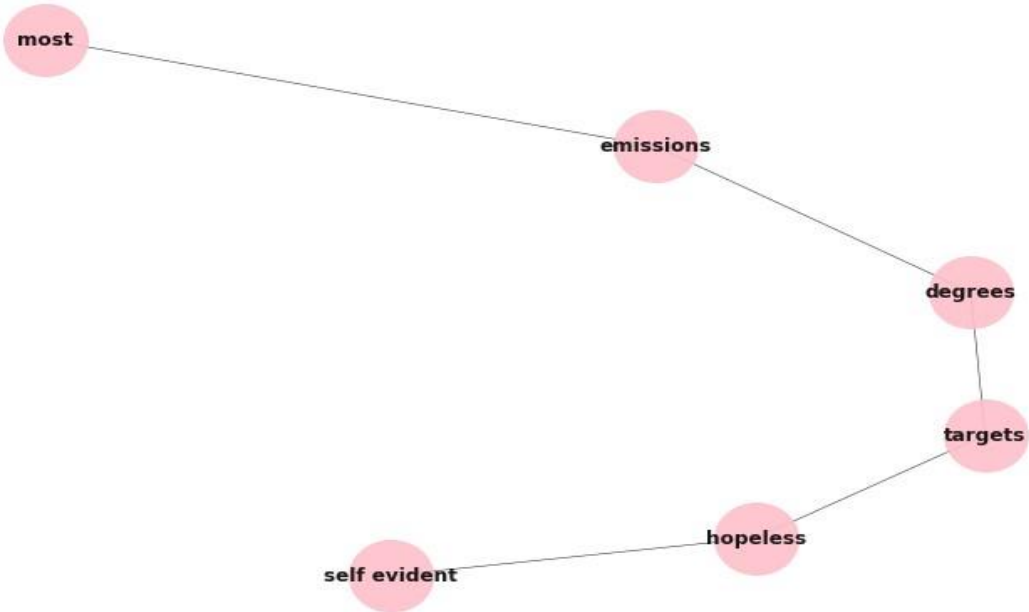
Example 4 TFIDF:



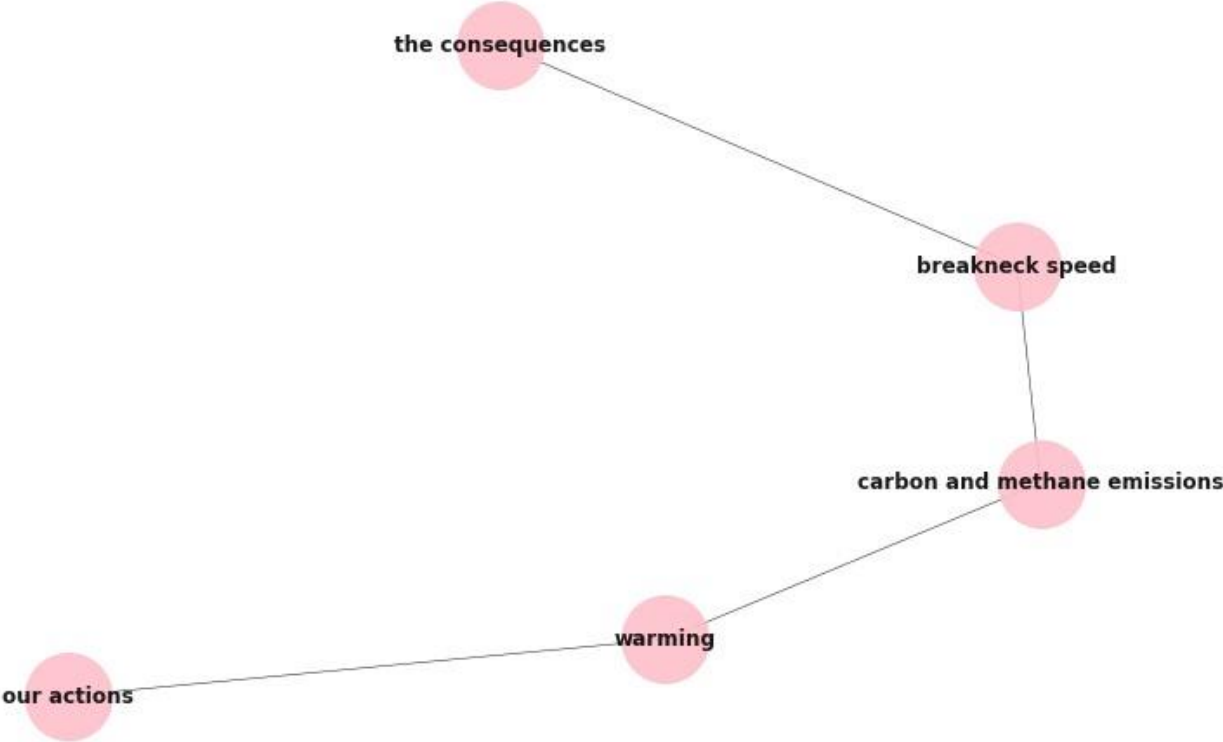
Topic Rank:



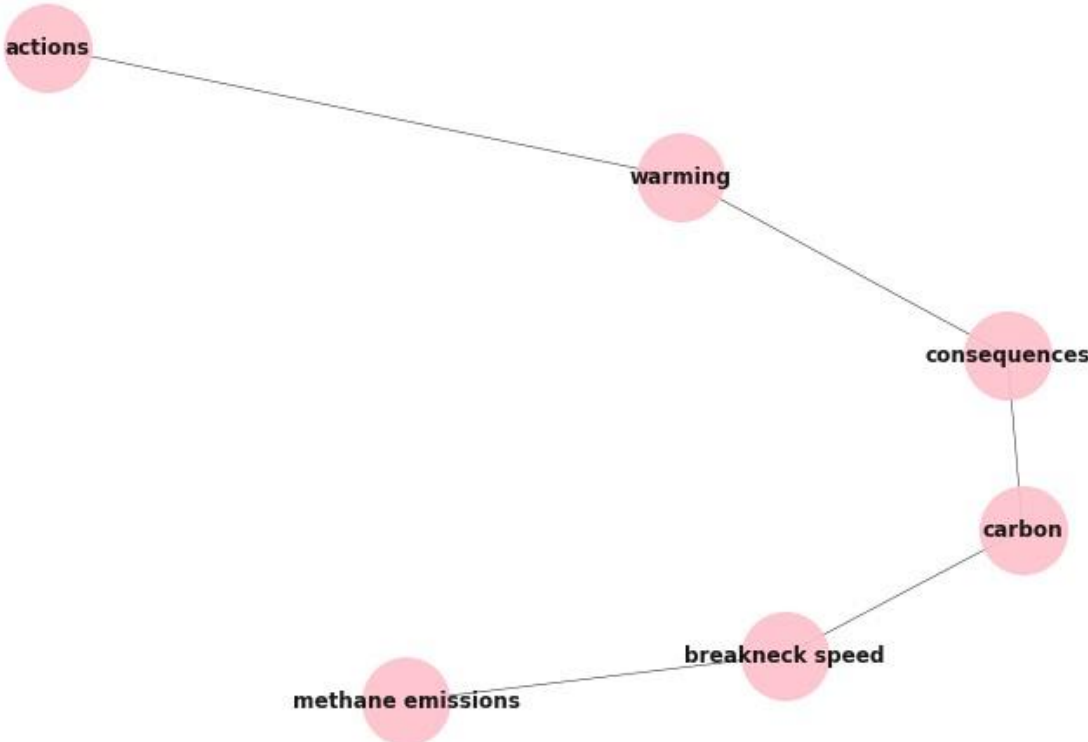
Text Rank:



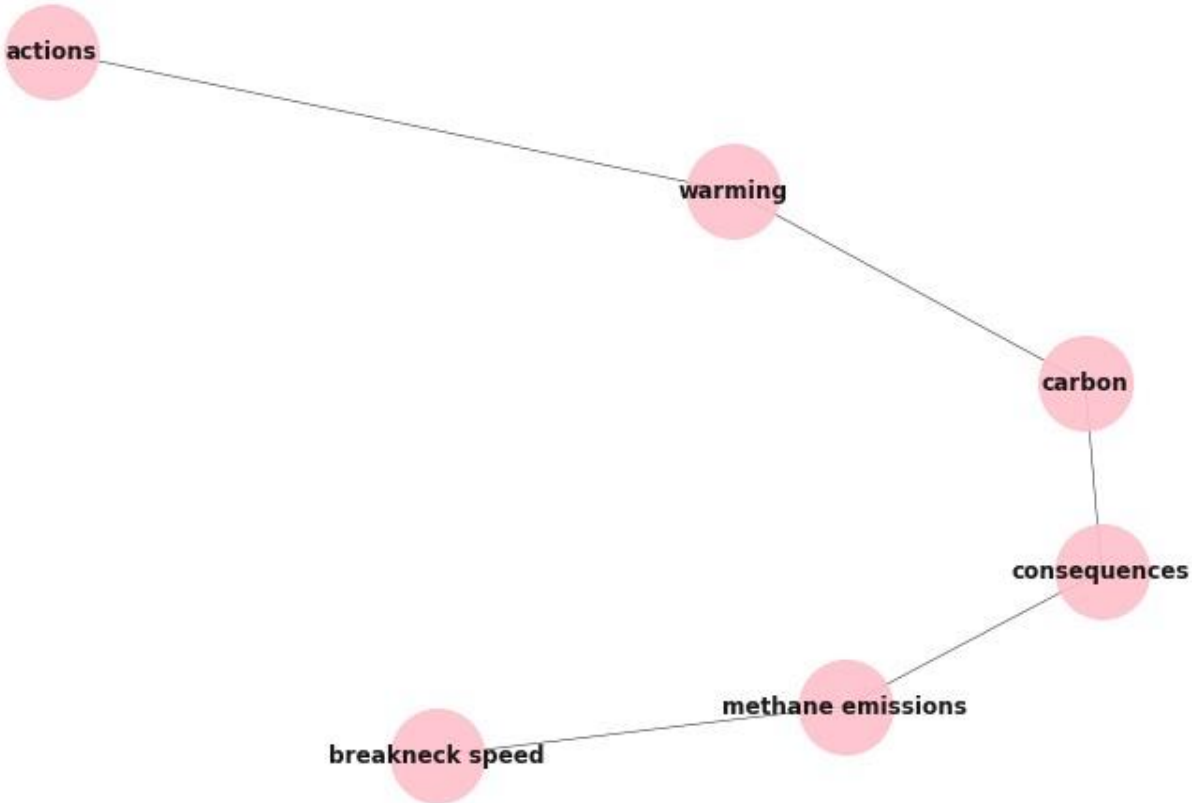
Example 5 TFIDF:



Topic Rank:



Text Rank:



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