

Syracuse University

SURFACE at Syracuse University

Dissertations - ALL

SURFACE at Syracuse University

8-4-2023

Framing, Emotions, Saliency: The Future Of Ai As Seen By Redditors

Ayse Ocal
Syracuse University

Follow this and additional works at: <https://surface.syr.edu/etd>

Recommended Citation

Ocal, Ayse, "Framing, Emotions, Saliency: The Future Of Ai As Seen By Redditors" (2023). *Dissertations - ALL*. 1823.

<https://surface.syr.edu/etd/1823>

This Dissertation is brought to you for free and open access by the SURFACE at Syracuse University at SURFACE at Syracuse University. It has been accepted for inclusion in Dissertations - ALL by an authorized administrator of SURFACE at Syracuse University. For more information, please contact surface@syr.edu.

ABSTRACT

With today's advanced technological improvements, the usage of various Artificial intelligence (AI) applications is still growing. This dissertation seeks to uncover how the future of AI is perceived by the social media users through the lens of *technological frames* and how these perceptions shape users' emotions, attitudes, and the level of engagement stemming from salience of the frames. This shaping process is considered a type of *social influence*.

The concept of *technological frame* is defined briefly as the interpretations, assumptions, expectations, and knowledge that people have about technology. Prior research suggests frames affect emotions and attitudes, and emotions and attitudes in turn affect peoples' level of engagement. Even though many questionnaires and interviews have been conducted to understand the public's attitudes towards AI and their relevant beliefs and views, many of these endeavors were not grounded on a theory and overlooked the connections between frames and emotions towards AI.

On the grounds of framing theory and affective intelligence theory, this work investigates technological frames expressed in social media conversations where many users freely share their most recent ideas. The specific focus is Reddit, a huge social media platform that attracts millions of users with diverse mentalities shaped by different backgrounds, prior beliefs, personal experiences and personalities, from various geographical locations, thereby bringing different segments of the public together. More specifically, a corpus consisting of 998 unique future of AI-related post titles and their corresponding 16,611 comments created between 2012 and 2022 by 671 unique Redditors (Reddit users) was analyzed by using computer-aided textual analysis comprising a BERTopic model, and two BERT text classification models, one for emotion and the other for sentiment analysis, supported by human judgment. Finally,

relationships among technological frames, emotions, attitudes, and the number of comments were examined to test a research model.

The findings showed different interpretations about the power of AI and concerns such as possible justice and ethical problems stemming from AI usage (e.g., lack of laws, and privacy, bias, discrimination issues). However, the general attitude towards the future of AI was slightly positive and the most common feeling was curiosity. Moreover, the findings confirmed the research model we proposed and showed that technological frames affect social influence. More specifically, for example, we found that Benefits frame is positively related to curiosity and positive attitude.

This original work makes several main contributions. As a practical contribution, the findings of this analysis can enrich current public voice-centric explorations of perceived future impacts of AI such as its benefits and risks. Also, the exploration of drivers of social influence in the context of technology may be useful for building awareness in society to accelerate the deployment and development of technologies for good of society. This study also provides policy implications. Academia, industry and government communities can collaborate to support policy arrangements in the areas where misconceptions about the future of AI are widespread. As theoretical and methodological implications, we propose a theoretical model and harness computer-aided textual analysis, which is applicable to further research. Lastly, this work helps us understand human communication in a technology setting focusing on frames, emotions and attitudes which are several elements that make us social creatures and develops computational language technologies that can discern these social elements in social media text data, thus constituting a bridge that connects fields of information systems, computational science and empirical social research.

FRAMING, EMOTIONS, SALIENCE: THE FUTURE OF AI AS SEEN BY REDDITORS

by

Ayse Ocal

B.S., Hacettepe University, 2012

M.S., Hacettepe University, 2014

M.S., Hacettepe University, 2015

M.S., Syracuse University, 2018

Dissertation

Submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Information Science and Technology

Syracuse University

June 2023

Copyright © Ayse Ocal 2023

All Rights Reserved

ACKNOWLEDGEMENTS

With enormous pleasure, I want to express my sincere and deepest gratitude to my great advisor, Prof. Kevin Crowston, for his immense support, patience, and excellent guidance through my Ph.D. His excellent research and intelligent advising skills helped me complete every step successfully in this challenging journey where I grew a lot as a researcher. His work ethic, discipline and effective teaching methods led me to become an independent researcher and will be an example to follow when I start to educate my students. I simply cannot thank him enough for his endless support, kindness, guidance, and encouragement. Prof. Crowston is the best advisor and the nicest person in the world. Thank you so much, Prof. Crowston!

I am also grateful to Prof. Carsten Østerlund because of his support during my master's and his introduction me to Prof. Crowston. I would like to thank Prof. Caroline Haythornthwaite and Prof. Jason Dedrick for their support during my master's and for Ph.D. application process. I am also deeply thankful to Dr. Lu Xiao for her guidance, support and kindness. I'm very thankful to my dissertation committee members Prof. Bei Yu, Dr. Daniel Acuna, Dr. Josh Introne and Dr. Keren Henderson. They have provided crucial feedback to enhance my dissertation. I also thank Prof. Steve Sawyer and Prof. Bei Yu who supported me through their wisdom and kindness as the doctoral directors. I want to thank other faculty members I had the chance to work with or to have conversations about my teaching and research during my Ph.D. journey: Prof. Jenny Stromer-Galley, Prof. Bruce Kingma, Dr. Nancy McCracken, Dr. Jasmina Tacheva, Dr. Jeff Saltz, Prof. Jeff Stanton, Dr. Jeff Hemsley, Dr. Ingrid Erickson, Dr. Bryan Seeman, Prof. Ping Zhang and Dr. Sevgi Erdogan.

I thank all the other faculty members and staff at the iSchool for their insightful conversations and support. I also thank to Women in Science and Engineering and graduate

school programs to support us through beneficial events. Furthermore, I have met wonderful friends at the iSchool who are like sisters and brothers whom I'm thankful: Daniela Fernández Espinosa, Shivali Naik, Sucheta Lahiri, Subhasree Sengupta, Qingyu Liang, Han Zhuang, Lizhen Liang, Amira Rezgui, Mabi Harandi, Isabel Munoz, Jieun Yeon, Christy Joseph Khoury, Pyeonghwa Kim, Charis Asante-Agyei, Qunfang Wu, Yisi Sang, Leah Therese Dudak, Sarah Bratt, Sarah Bolden, Jennifer Sonne, Corey Jackson, Alexander Smith, Jean Philippe Rancy, Nata Barbosa, and Yaxing Yao.

Last but not least, I had the privilege to attend WAIM conference and to discuss the proposal of this dissertation in the summer 2022. I sincerely appreciate Prof. Youngjin Yoo, Dr. Peter Denno and Dr. Nicholas Diakopoulos for their valuable comments. Also, two master's students, Archana Deshpande and Kanishk Gupta, helped me for labelling and classifying the categories for validating the results of this dissertation. I am so thankful for their contributions.

I am also fortunate to have many incredible Turkish friends and I express my gratitude to all of them. I also thank my Turkish professors in my former school, Hacettepe University. They encouraged me to follow my dream and pursue my Ph.D. degree. I also express my sincere and deep gratitude to Turkish Ministry of Education. Thanks to their support, I had the opportunity to come to the USA and became the researcher and person that I am today.

Lastly, I am deeply thankful to the people who are the most valuable in my life: my mother, father, and brother, Hatice Ocal, Ismail Ocal and Hayri Ocal for their endless lifelong love, support, and caring, to whom I dedicate this dissertation.

Son olarak, hayatımdaki en değerli kişilere, anneme, babama ve abime: Hatice Öcal, İsmail Öcal ve Hayri Öcal, ömür boyu süren sonsuz sevgileri ve destekleri için derinden teşekkür ediyorum. Bu tezi onlara ithaf ediyorum.

TABLE OF CONTENTS

| | |
|---|----|
| ACKNOWLEDGEMENTS | v |
| LIST OF TABLES | ix |
| LIST OF FIGURES | x |
| CHAPTER 1. INTRODUCTION | 1 |
| 1.1. Background and Motivation..... | 1 |
| 1.2. Problem Statement | 5 |
| 1.3. Research Questions | 8 |
| 1.4. Dissertation Overview..... | 8 |
| 1.5. Included Studies | 9 |
| 1.5.1. Technological Frames on Social Media: What do Redditors Think of the Future of AI? (Study 1) | 9 |
| 1.5.2. Emotions and Attitudes: How do Redditors Feel about the Future of AI? (Study 2).. | 11 |
| 1.5.3. Influence in Social Media: An Investigation of the Future of AI on Reddit (Study 3) | 12 |
| CHAPTER 2. LITERATURE REVIEW | 14 |
| 2.1. Introduction | 14 |
| 2.2. Framing | 14 |
| 2.3. The Effects of Framing on Social Influence | 17 |
| 2.3.1. The Effects of Framing on Attitudes, Emotions and Behaviors..... | 18 |
| 2.4. Framing Technology | 21 |
| 2.4.1. Technological Frames..... | 22 |
| 2.5. Research Model and Hypotheses | 34 |
| CHAPTER 3. METHODOLOGY | 41 |
| 3.1. Introduction | 41 |
| 3.2. Research Site: Reddit | 42 |
| 3.2.1. Selection of Subreddits | 44 |
| 3.3. Data Collection and Cleaning | 45 |
| 3.4. Data Analysis | 48 |
| 3.4.1. Frame Identification | 48 |
| 3.4.2. Discerning Emotions and Attitudes..... | 54 |
| 3.4.3. Pilot Study | 55 |

| | |
|---|-----|
| 3.4.4. Main Studies | 60 |
| CHAPTER 4. FINDINGS..... | 68 |
| 4.1. Introduction | 68 |
| 4.2. Study 1 –Technological Frames on Social Media: What do Redditors Think of the Future of AI?..... | 68 |
| 4.3. Study 2 – Attitudes and Emotions Discerned in Reddit Submissions | 73 |
| 4.4. Study 3 – Social Influence on Reddit..... | 78 |
| 4.5. Summary of Findings..... | 89 |
| CHAPTER 5. CONCLUSION..... | 93 |
| 5.1. Discussion | 93 |
| 5.2. Implications, Limitations, and Future Directions..... | 97 |
| 5.2.1. Practical Implications and Relevant Suggestions for Future Research | 97 |
| 5.2.2. Theoretical Implications and Relevant Suggestions for Future Research..... | 100 |
| 5.2.3. Policy Implications and Relevant Suggestions..... | 104 |
| 5.2.4. Methodological Implications | 105 |
| 5.3. Limitations | 106 |
| 5.4. Future Research Projects | 107 |
| 5.5. Conclusion..... | 108 |
| APPENDICES | 111 |
| APPENDIX A..... | 112 |
| Preliminary Results Obtained from the Pilot Study..... | 112 |
| APPENDIX B | 124 |
| Frame Identification Procedure..... | 124 |
| APPENDIX C | 155 |
| Annotation Protocol | 155 |
| APPENDIX D..... | 165 |
| Annotation Results..... | 165 |
| REFERENCES | 169 |
| Curriculum Vitae | 184 |

LIST OF TABLES

| | |
|---|----|
| Table 1. Key Elements in the Emotion Sequence (Plutchik, 1980, p. 16, 2000, p. 69)..... | 19 |
| Table 2. Research on Technological Frames and related Research on Technological Artefacts (Adapted from Spieth et al., 2021, p. 1967)..... | 25 |
| Table 3. AI-related Technological Frames based on the Existing Literature | 33 |
| Table 4. Social Influence Sequence in Technology-related conversations..... | 40 |
| Table 5. Information about Subreddits | 44 |
| Table 6. Chi Square Post Hoc Tests Results for the Relationship between Frames and Sentiments | 80 |
| Table 7. Chi Square Post Hoc Tests Results for the Relationship between Frames and Emotions | 82 |
| Table 8. Negative Binomial Regression for the Relationship between Emotions in Posts and Saliency..... | 85 |
| Table 9. Negative Binomial Regression for the Relationship between Sentiments in Posts and Saliency..... | 87 |
| Table 10. Negative Binomial Regression for the Relationship between Frames in Posts and Saliency..... | 88 |
| Table 11. Chi Square Post Hoc Tests Results for the Relationships Between Frames in the Post Titles and Frames in the Comments..... | 89 |
| Table 12. Social Influence Sequence in Technology-related Conversations (Modified Hypotheses)..... | 90 |
| Table 13. Social Influence Sequence in Technology-related Conversations (Based on Findings) | 92 |

LIST OF FIGURES

| | |
|---|-----|
| Figure 1. Research Model..... | 35 |
| Figure 2. The Number of Posts by Years and Subreddits..... | 47 |
| Figure 3. The Number of Comments by Years and Subreddits..... | 47 |
| Figure 4. Data Analysis Steps..... | 61 |
| Figure 5. Attitudes Observed in the Entire Data Set..... | 74 |
| Figure 6. Emotions Observed in the Entire Data Set..... | 75 |
| Figure 7. Distribution of the Number of Comments among Emotion Categories in the Posts | 84 |
| Figure 8. Distribution of the Number of Comments among Sentiments in the Posts..... | 86 |
| Figure 9. Distribution of the Number of Comments among Frames in the Posts..... | 88 |
| Figure 10. Final Research Model..... | 100 |

CHAPTER 1. INTRODUCTION

1.1. Background and Motivation

“Scientific progress may accelerate when artificial intelligence (AI) will explore data autonomously, without the blinders imposed by human prejudice” (Futurology Subreddit, 2021).

“What is to Fear? What should worry us most about artificial intelligence: losing our jobs to cheaper labor or losing our lives to killer robots? The real threat may lie in yet another danger: losing our minds” (Conspiracy Subreddit, 2020).

These two quotations from two Reddit subreddits outline different interpretations of the future of artificial intelligence (AI) in society. The first quotation is an optimistic point of view — the interpretation of “AI will explore data without human prejudice” suggests that AI will be fairer than humans while exploring data—whereas the second quotation is a pessimistic point of view—highlighting in addition to previously-stated AI-related fears such as losing jobs or lives, a new dystopian interpretation of losing minds. Which AI-related interpretations are more common in public conversations? What is the emotional responses to these interpretations? How do individuals’ interpretations generate social influence?

AI has been an exciting topic in popular culture for a while. With today’s advanced technological improvements, the usage of various AI applications is still growing all around the world from governments, large organizations, small businesses to the public, and even now much more advanced AI applications are still emerging. A survey reported that 80% of companies are using AI applications in their production (Chuan et al., 2019; TeraData, 2017). The public also uses various AI applications, from smart voice assistants to self-driving cars. For example, 70% of smartphone owners use a voice assistant on their device (Voicify, 2019).

Advancements in AI change modern life by reforming transportation, health, science, finance, and the military (Grace et al., 2018). Despite AI's stream of successful applications in various domains, many questions concerning its social, economic, political, and ethical impacts, deployment and development arise, thus causing uncertainty about its trajectory. This signals a critical need to understand the public's relevant views about AI because the public's perceptions and attitudes towards technology are important for social accepting, adopting, shaping the development and deployment of that technology (Neudert et al., 2020), research funding, commercial development, regulation (Kelley et al., 2021) and policies, adapting to changes and policies, and addressing uncertainty about its trajectory. Social accepting, adopting, and shaping of the development of technological tools depends on the interpretations of the technological advancement's benefits, limitations, and risks (Chuan et al., 2019). During these interpretations processes, actors rely on their cognitive schemas reflecting what features of technology they focus on (Spieth et al., 2021), termed as *technological frames* (Orlikowski & Gash, 1994; Spieth et al., 2021).

Orlikowski and Gash (1994) developed the concept of *technological frames*, referring to cognitive structures (i.e., assumptions, expectations, and knowledge) that people have about technology, which subsequently serve to shape general understanding of the technological advancement's power, limitations, and risks and subsequent attitudes and behaviors towards it (Orlikowski & Gash, 1994). The notion of *framing*, in general, refers to "processes by which people develop a particular conceptualization of an issue or reorient their thinking about an issue" (Chong & Druckman, 2007, p. 102). Peoples' own conceptualizations of interpreted reality are "frames in thought" and "frames in communication" shared through speech or writing (Chong & Druckman, 2007; Stecula & Merkle, 2019) are reflections of "frames in thought."

In this dissertation, to understand how the future of AI is viewed by the public and how these views shape their emotions and attitudes, I examine *technological frames* for AI, i.e., *AI frames*. By *AI frames*, I refer to individuals' perceptions, interpretations, beliefs, assumptions, and expectations about AI technology shared through speech and writing. I observe these AI frames embedded in writing, in text, in particular, in social media, Reddit submissions (i.e., Reddit posts and comments).

Social media platforms constitute socio-technical systems connecting communities of humans together with technology to engage in conversations as a modern form of Information and Communication Technologies (ICTs) (Venkatesan & Valecha, 2021). These platforms have played an active role in diffusing frames about various social events and phenomena, thus accelerating to view them from different perspectives and to construct social influence.

Social influence is defined as our “thoughts, feelings, and behaviors [that] respond to our social world” (Heinzen & Goodfriend, 2019, p. 3). The Twitter hashtag #MarchForOurLives, for example, was distributed more than three million times, through which the social phenomenon of gun control was discussed by millions and this facilitated social influence (Venkatesan & Valecha, 2021). Thus, social media plays an important role in the development of frames and some frames may be drivers of social influence (Venkatesan and Valecha, 2021).

Prior work has been analyzed social influence on Twitter (e.g., Garcia et al., 2017; Venkatesan & Valecha, 2021; Ye & Wu, 2010). Most of that research has measured social influence by the number of retweets, and deemed frames as potential social influence drivers on Twitter during events such as Egyptian Revolution of 2011 and March for Our Lives which was a student-led demonstration event for supporting of gun control legislation. Venkatesan and Valecha (2021) suggest retweet motivation can be associated with many factors including

engaging a particular audience and commenting on a content. On the other hand, Entman (1993) defines *salience* as making a piece of information more noticeable, meaningful, or memorable to audiences. If a post is more *salient*, namely it is more noticeable, the level of engagement is expected to be higher.

Conversations about AI also involve social elements, thus they may construct social influence. Losing employment due to AI, for example, is not merely an economic problem; it also causes a variety of social and psychological impacts (Stahl, 2021), and discussions around such kinds of impacts may build social influence. Referring to Heinzen and Goodfriend's (2019) social influence definition, this study analyzes relationships among *frames*, *emotions*, *attitudes*, and *commenting behavior*, specifically *salience* in social media where social influence is frequently observed. This research proposes a comprehensive standpoint that inspects the roles of frames, emotions, attitudes, and commenting behavior in social influence as a natural process in social media.

As regards to theoretical importance of this study, this research discusses how the public interprets *the future of AI* through the lens of technological frames established in Information Systems (IS) community and the drivers of users' social influence in technology-related conversations drawing on framing theory and affective intelligence theory. Research in the both communities of IS (e.g., Venkatesan & Valecha, 2021) and Computer Supported Cooperative Work (CSCW) and CHI (Human–Computer Interaction) has examined how crowds sustain or restrain social influence utilizing ICTs (Wu et al., 2022).

This interdisciplinary work appealing also to CSCW and CHI communities can contribute to the expansion of IS knowledge through presenting public views in social media constituting collectives at the intersection of technological and social impacts of AI, and through

examining possible associations among frames, emotions, attitudes, and commenting behavior by computational methods. This dissertation reviews varied methods utilized for identifying frames, emotions and attitudes to determine the most appropriate method for each identification task and applied them on a large amount of text data. Thus, it constitutes a bridge that connects the fields of IS, computational science and empirical social research. Moreover, this study presents both qualitative and quantitative results in a harmony, which enriches the content of the findings.

Understanding public views circulated in the social media through the lens of technological frames can help to take effective and right future steps to meet the necessities to adapt relevant public policies and to develop appropriate AI applications, mitigate weaknesses of AI and solve relevant problems based on public perceptions. Furthermore, the possible drivers of social influence in technology conversations may be useful to increase the awareness of the society about the technology. This research aims to yield empirical findings grounded on theories and conceptual phenomena (e.g., technological frames, social influence).

1.2. Problem Statement

Many surveys and interviews have been conducted to understand the public's attitudes towards AI and their relevant beliefs and interpretations (e.g., Grace et al., 2018) to discuss policy arrangements or to navigate the deployment and development processes of AI applications, but many of these endeavors overlooked the connections between the interpretations and emotions and attitudes towards AI. Moreover, information obtained from surveys and interviews was generally limited to the questions determined in the research design, respondents' understandings of these questions and the time when these surveys or interviews were conducted. Thus, in this dissertation, on the grounds of framing theory and affective intelligence theory,

benefiting from the concept of *technological frames*, I discern interpretations and feelings about the future of AI by analyzing social media data shared by the users freely. Technological frames provide effective analytic perspective for explaining and anticipating situations that are not simply gained with other theoretical lenses (Orlikowski & Gash, 1994).

Many academic and industrial surveys and interviews, many science fiction movies, futurists, media, and novels have handled AI's power, concerns which illustrate existing or emerging general disputes such as the impact of automation on the future of work (Brynjolfsson et al., 2014; Kelley et al., 2021), human rights and ethical problems stemming from AI usage (e.g., privacy, bias, discrimination) and emotions such as fears and enthusiasm (Chuan et al., 2019), which may also cause others to internalize these disputes or emotions as a result of social influence (Gass, 2015) may be facilitated by ICTs (Venkatesan & Valecha, 2021) such as social media.

As social media becomes more and more ingrained in our daily lives, research on posts and discussions on social media is a way of understanding the transmission of information and the general public's views on an issue or event (Villanueva, 2021). Social media is a convenient, comfortable, and fluid tool (Öcal et al., 2021) for advocacy, activism, and presenting salient issues for everyday users (Villanueva, 2021). Many individuals obtain their news from social media and share their news or ideas with others on social media platforms (Öcal et al., 2021). Social media users come from different segments of the public and have a range of mindsets with various backgrounds, personal experiences, personal traits, and emotions and attitudes towards AI. Thus, exploring a possible social influence on such platforms may be quite effective.

Social influence is communication that affect the others' attitudes, emotions, beliefs, intentions, motivations, or behaviors (Gass, 2015). Some studies have viewed emotions as

consequences of frames, such as Brewer (2001) and Gross and D'Ambrosio (2004). Frames and emotions are in turn seen as precursors to attitudes and behaviors, in studies such as Brockner and Higgins (2001) and Stam and Stanton (2010), which I explain in more detail in the literature review chapter. On the other hand, framing theory suggests that frames make the content more salient (Entman, 1993), which means basically being noticeable, in other words, gaining more attention, which is attributed to the level of engagement (as in Choi et al., 2021), which is associated with social influence (Venkatesan & Valecha, 2021).

Research on AI framing (e.g., Chuan et al., 2019; Duberry & Hamidi, 2021; Fast & Horvitz, 2017), however, has so far overlooked emotional and attitudinal connections to AI frames. But even looking at the two examples at the beginning of the introduction chapter, two different interpretations demonstrating how AI is framed by two different perspectives, include emotional aspects exhibited by words such as *fear*. Clearly, emotional appeals are part of or consequences of the frames (Gross & D'Ambrosio, 2004). Thus, AI frames may create social influence, and the failure to investigate the possible social influence of AI frames causes a gap in the literature.

This dissertation investigates whether technological frames create social influence through looking at the possible effects of AI frames in post titles on emotional and attitudinal responses and commenting behavior. Exploration of drivers of social influence in social media in the context of technology may be helpful for building awareness in society to facilitate deployment and development of technologies for good of society and to hinder the use of technologies that tend to cause dangers to society.

1.3. Research Questions

The purpose of this research is to explore how the public frames the *future of AI* on the light of the concept of *AI frames* and how these frames affect social influence. The following research questions guide this dissertation:

RQ1: How do social media users frame the future of AI?

RQ2: Which emotions and attitudes do social media users convey in the future of AI-related conversations on social media?

RQ3: How do AI frames affect social influence on Reddit?

1.4. Dissertation Overview

This dissertation is organized to consist of three studies. Section 1.5. Included Studies articulates the details of these studies. The remaining dissertation is established as follows. In Chapter 2, I first review studies related to frames, technological frames, and theories of framing and affective intelligence to build a theoretical foundation for the dissertation. Chapter 3 describes the methodology for the dissertation, the methods to be utilized for collecting and analyzing data to answer the research questions. Chapter 4 presents the results of the studies. Chapter 5 concludes the dissertation with discussion, research contributions, implications, and limitations.

1.5. Included Studies

The dissertation is composed of three related but separate studies. The details of each study are provided below.

1.5.1. Technological Frames on Social Media: What do Redditors Think of the Future of AI? (Study 1)

Using the concept of technological frames, the first study explores perceptions, interpretations, beliefs, assumptions, and expectations that people share on Reddit posts and comments about the future of AI. This study addresses these research questions: *How does social media frame the future of AI?*

To address these research questions, I examine AI frames. To discover commonly expressed AI frames in text I utilize topic modelling to analyze a sample of post titles and comments. More specifically, a corpus consisting of 998 unique future AI-related post titles and their corresponding 16,611 comments created between 2012 and 2022 by 671 unique Redditors was analyzed by using advanced computer-aided textual analysis methods comprising a BERTopic model supported by human judgment. We interpreted topic modelling results and categorized the relevant clusters of posts and comments into *risk*, *benefit*, *harm*, and *new world of work* frames.

This study makes several main contributions. As a practical contribution, the findings of this analysis can enrich current public voice-centric explorations of perceived future impacts of AI such as its benefits and risks, through the lens of technological frames on social media. As a further practical implication, these findings could help designing suitable interfaces that allow proper human-AI task coordination and collaboration, deploying innovative solutions for concerns to be revealed, developing more useful AI applications, mitigating weaknesses in AI

applications' necessary domains, and addressing ethical concerns (privacy, bias etc.) to maximize its benefits to society and minimize its potential harms.

Second, this study also provides research and policy implications. Expected outcomes can demonstrate areas where misconceptions and unrealistic interpretations about the future of AI are widespread, which may trigger speculative fears or concerns. AI experts anticipate developments in AI will alter modern life by reshaping transportation, health, science, finance and the military (Grace et al., 2018). This reshaping also may alter the future where we communicate, work, and live with each other and with intelligent machines (systems enhanced by AI), which requires competencies like understanding of “AI’s Strengths & Weaknesses,” “Imagine Future AI” and this set of competencies defined as *AI literacy* (Long & Magerko, 2020, p. 4). Researchers may be encouraged to more focus on the areas where misconceptions and lack of understandings are more common; additional research investments may be provided; educational programs may be arranged to increase AI literacy and speculative fears or concerns or take necessary measures for real potential risks. This study’s findings comprising public anticipations can also help to properly adjust relevant public policies. Academia, industry, and government communities can collaborate to support research and policy arrangements in those areas.

Third, as a methodological implication, harnessing computer-aided textual analysis that combines topic modelling with human judgment, this study reveals frames embedded in posts and comments shared by Redditors with diverse mentalities shaped by different backgrounds, prior beliefs, personal experiences and personalities to showcase latest perceptions about the future of AI from many different public viewpoints. This method may be an example method for relevant future research studies.

1.5.2. Emotions and Attitudes: How do Redditors Feel about the Future of AI? (Study 2)

As prior research suggests frames affect emotions and attitudes (e.g., Brockner & Higgins, 2001), the second study seeks to discern both emotions and attitudes embedded in the future of AI- related posts and comments. Moreover, Marcus (2013) articulates emotions and attitudes affect peoples' mode of engagement and their mode of decision-making, thus increasing the importance of investigating emotions and attitudes. This study aims to answer these research questions: *Which emotions and attitudes does the public convey in the future of AI-related conversations on social media?*

For finding emotions, I fine-tuned a pre-trained BERT model for multiclass text classification using GoEmotions dataset (Demszky et al., 2020) through ktrain, which is a lightweight wrapper for the deep learning libraries such as TensorFlow and Keras to help build, train, and deploy neural networks and machine learning models (Maiya, 2022). The GoEmotions dataset is a manually annotated dataset of 58k English Reddit comments (Demszky et al., 2020), labelled for 27 emotion categories or Neutral. The emotion categories in this dataset are admiration, amusement, anger, annoyance, approval, caring, confusion, curiosity, desire, disappointment, disapproval, disgust, embarrassment, excitement, fear, gratitude, grief, joy, love, nervousness, optimism, pride, realization, relief, remorse, sadness, surprise. I built a model to capture all these 28 categories in text. To explore *positive* and *negative* attitudes, I harness another BERT model fine-tuned with the IMDb Movie Reviews Dataset consisting of 50k movie reviews.

The outcomes of this study can provide implications for practice, methods, and future research. Revealing emotions and attitudes towards the future of AI may shed light on future AI innovations, human-AI interaction design, human-AI symbiotic work design that allocates

coordination and collaboration tasks between humans and AI through focusing also on humans' emotions and attitudes. As a methodological implication for future research, this study evaluates varied methods to discover the proper methods for detecting emotions and attitudes and applied them on a large amount of text data, which may illuminate scholars with similar research purposes for further related research.

1.5.3. Influence in Social Media: An Investigation of the Future of AI on Reddit (Study 3)

The third study proposes an integrated theoretical research model established by relevant theories and previous literature with the intention of testing it in a technology setting. This model examines relationships between frames, emotions, attitudes, and commenting behavior. The study addresses this research question: *How do AI frames in sociotechnical systems like Reddit impact social influence (i.e., emotions, attitudes, and commenting behavior)?*

To answer these questions, I conduct statistical analyses to test the proposed research model harnessing frames, emotions, and attitudes found in the first and second studies, and commenting behavior, more specifically, the number of comments as the indicator of the level of engagement as in Choi et al. (2021), thereby salience of the posts (Entman, 1993).

The outcomes of this study can provide practical, theoretical, and methodological implications. As a practical implication, exploration of drivers of social influence in socio-technical systems such as social media in the context of technology may be useful for building awareness in society to accelerate deployment of technologies for good of society as well as to hinder the use of technologies that tend to cause dangers to society. As theoretical implication, this study proposes a theoretical model that can be applicable for other cognition-emotion-attitude-behavior related research. This study observes social influence through analyzing frames

in post titles and emotions and attitudes in comments in addition to the number of comments.

This method may be effective to examine social influence in other situations or events.

CHAPTER 2. LITERATURE REVIEW

2.1. Introduction

This literature review synthesizes previous research on frames, technological frames, AI frames, and emotional and attitudinal responses to framing. The first section in this chapter presents a brief overview of framing and Entman's (1993) framing theory. The next section describes social influence by making emotional and attitudinal connections with frames through the lens of framing theory, Affective Intelligence Theory, and Plutchik's (1980) general psychoevolutionary theory. The third section reviews the technological frames literature, discusses frames in the context of AI, and presents AI frames obtained from the previous relevant literature. The last section concludes the chapter with an integrated research model and hypotheses proposed based on the prior literature and mentioned theories.

2.2. Framing

The notion of *frame* was first used in 1937 by the theorist Kenneth Burke who defines frames as “major psychological devices whereby the mind equips itself to name and confront its situation” (Wood et al., 2018, p. 248). After Burke, in 1952, the anthropologist Gregory Bateson employed the notion to examine monkeys' behaviors (Wood et al., 2018). Observing the monkeys' behaviors at the Fleishhacker Zoo, Bateson claimed that monkeys have “psychological frames” for a “real fight” and a “play fight” and give different reactions to these two frames (Wood et al., 2018). Later, the notions of *frame*, *frameworks*, and *framing* (the process of constructing and employing frames) were used in various research domains, e.g., in sociology (Goffman, 1974), psychology (Tversky & Kahneman, 1975) and communication (Entman, 1993).

The sociologist Erving Goffman (1974) utilized the concept of framework for the *frame* concept and described *primary frameworks* as “schemata of interpretation” that allow users “to

locate, perceive, identify, and label” events or situations in their world (Goffman, 1974, p. 21). Goffman proposed two types of frameworks: natural and social. Goffman (1974) suggests natural frameworks exist naturally, and they are not guided; but on the other hand, “social frameworks provide background understanding for events” and social frameworks is the social context “that incorporate the will, aim, and controlling effort of an intelligence, a live agency, the chief one being the human being” (p. 23). And according to Goffman (1974), “such an agency is anything but implacable; it can be coaxed, flattered, affronted, and threatened. What it does can be described as ‘guided doings’” (p. 23).

In psychology, two prominent framing-related studies by Plous (1993) and Tversky and Kahneman (1975) presented empirical data from decision making scenarios to observe how language choice manipulates risky decisions. Plous (1993) and Tversky and Kahneman (1975) associated framing with cognitive bias through manifesting the manipulation effect of formulating problems framed by different wordings. Tversky and Kahneman (1975) suggest different frames (e.g., losses and gains) used for formulating the same problems alter respondents’ preferences (Plous, 1993). These differences may stem from a match between frames in thought arising cognitive bias in respondents’ minds and framing presented in the problems. Tversky and Kahneman (1975) suggest changing frames alter preferences of respondents exposed to different frames (e.g., losses and gains) used for formulating the same problems (Plous, 1993). These differences may stem from a match between frames in thought arising cognitive bias in respondents’ minds and framing presented in the problems.

Chong and Druckman (2007) indicated the existence of two forms of frames: frames in thought and frames in communication (i.e., frames shared through speech and text). “Frames in thought” can influence individuals’ overall opinion (for example, a free speech frame prompts a

person to support a group's right to act). Many politicians try to influence voters to consider policies to support their positions (Chong & Druckman, 2007). This goal is achieved by emphasizing the specified aspects of these policies, such as their possible outcomes or their connections to salient values, thereby the speaker induces a "frame in communication" (Chong & Druckman, 2007).

Robert Entman (1993) provides a universal understanding of *framing theory* by focusing more on its communication angle. *Framing theory* posits that ideas can be presented from various perspectives and individuals can reorganize their thinking around those ideas (Chong & Druckman, 2007) as Goffman (1974) stated frames work for "guidance doings." Thus, changes in framing alter interpreting of information or situation, which again changes the way they respond to this information (Villanueva, 2021). That is, the way by which information is introduced can alter the way of comprehending, interpreting, evaluating, making decisions and acting on an event, issue, situation or phenomena (Nabi, 2003).

Entman (1993) associated framing with selection and salience by emphasizing that framing helps to select some characteristics of a perceived reality and to make them more salient in communications. On the other hand, "judgments and attitude formation are directly correlated with [salience]" (Scheufele & Tewksbury, 2007, p. 11) and frames (e.g., losses and gains) make content more salient, in other words, easy to notice and increase the level of engagement (Entman, 1993).

Media plays an important role in selecting issues that are more salient in audiences' minds (agenda setting theory) and can influence how they perceive these issues (Scheufele & Tewksbury, 2007). Framing is a more advanced version of agenda setting; framing makes issues more salient through different modes of presentation (e.g., loss vs. gain, risk vs. benefit) and thus

changing individuals' attitudes (Scheufele & Tewksbury, 2007) and increasing the level of engagement (Entman, 1993). Agenda setting focuses on selecting stories that public tends to pay attention, while framing “focuses not on which topics or issues are selected for coverage by the news media, but instead on the particular ways those issues are presented” (Scheufele & Tewksbury, 2007, p. 15). These presentations influence attitudes and behaviors, which is considered framing effect and social influence. Today, social media in addition to traditional media, plays an important role in framing, and framing was found as one of the social influence drivers (as in Venkatesan & Valecha, 2021) as shown in the next section.

2.3. The Effects of Framing on Social Influence

Social influence is defined as our “thoughts, feelings, and behaviors [that] respond to our social world” (Heinzen & Goodfriend, 2019, p. 3). Some prior work conceptualized frames as public objects consisting of assembled components that constitute an “interpretive package” (Gamson & Modigliani, 1989), thereby frames can work as a public interpretative tool (Wood et al., 2018). Moreover, frames influence everyone exposed to them, regardless of the individuals' social status or experiences, but their responses to a specific frame may vary, thus frames always evoke responses from individuals (Wood et al., 2018). These responses may be thoughts, feelings, and behaviors, thus forming social influence, and social media is one of the most prominent platforms where social influence is observed.

Prior research indicates social media plays an important role in the development of frames publicly and some frames may be drivers of social influence (Venkatesan and Valecha, 2021). Social influence on Twitter has been extensively analyzed in the literature (e.g., Garcia et al., 2017; Venkatesan & Valecha, 2021; Ye & Wu, 2010). According to Venkatesan and Valecha (2021), many researchers have measured social influence by the number of retweets. Venkatesan and Valecha (2021) examined frames (i.e., social movement mobilization generic frames) as

potential social influence drivers on Twitter during the Egyptian Revolution of 2011 and contemplated retweets as the measure of social influence.

Referring to Heinzen and Goodfriend's (2019) social influence definition, framing and affective intelligence theories, I also examine *attitudinal* and *emotional responses to frames* as other potential social influence drivers and measurements. The following sections review prior work that shows how frames, attitudes, emotions, and behaviors are related.

2.3.1. The Effects of Framing on Attitudes, Emotions and Behaviors

Individuals' attitudes and behaviors, as well as their emotional responses to a message, are influenced by frames (Villanueva, 2021). On the other side, despite the fact that emotions and attitudes are different phenomena (Allen et al., 1992), emotions affect attitudes and behaviors (Brockner & Higgins, 2001; Nabi, 2003; Stam & Stanton, 2010). For example, if the same property is framed by a real estate agent as either "small" or "cozy," the frame of "cozy" lead people exposed to that frame to perceive this property more positively and to be more motivated to purchase it (Benschop et al., 2022). The reason behind such positive attitude and motivation to purchase it could be that "cozy" invokes warm emotions like trust. Wars, for instance, might be framed either as power protection or murders of children. These two frames could appeal to very different emotions like trust or sadness respectively. Many other similar examples can be given. Clearly, frames influence emotions (Gross & D'Ambrosio, 2004).

Emotions are "psychological responses of varying strength and duration that are evoked in response to an external stimulus" (Feldman & Hart, 2018, p. 586). Plutchik (1980) also highlighted "external stimulus" (e.g., threat, gain of valued object) as the trigger of the emotions in the general psychoevolutionary theory of emotion. Plutchik's (1980) general psychoevolutionary theory demonstrates the existence of relationships among cognition,

emotions, and behaviors. Table 1 quoted from (Plutchik, 1980, p. 16) and its slightly modified version in (Plutchik, 2000, p. 69) — I combined these two — depicts the development of emotions as linked with external stimulus, cognition, behavior and effect. This theory posits eight emotions: fear, anger, joy, sadness, acceptance, disgust, anticipation, and surprise.

Table 1. Key Elements in the Emotion Sequence (Plutchik, 1980, p. 16, 2000, p. 69)

| Stimulus event | Inferred cognition | Feeling | Behavior | Effect |
|-----------------------|--------------------|--------------|------------------|---------------|
| Threat | “Danger” | Fear | Escape | Protection |
| Obstacle | “Enemy” | Anger | Attack | Destruction |
| Gain of valued object | “Possess” | Joy | Retain or repeat | Reproduction |
| Loss of valued object | “Abandonment” | Sadness | Cry | Reintegration |
| Member of one’s group | “Friend” | Acceptance | Groom | Affiliation |
| Unpalatable object | “Poison” | Disgust | Vomit | Rejection |
| New territory | “What’s out there” | Anticipation | Examine | Exploration |
| Unexpected event | “What is it?” | Surprise | Stop, alert | Orientation |

Similar to Plutchik’s (1980) approach, Zajonc and Markus (1982) suggested that preferences may be grounded on both cognitive and affective factors in various combinations. In some situations, the cognitive factors may be dominant, in some situations the cognitive and affective factors may influence each other, and in other situations, the affective factors may be dominant (Zajonc & Markus, 1982). One example of cognitive factors may be frames.

Prior research has demonstrated the effects of frames on emotions. Many studies have considered emotions as consequences of frames (Yacoub, 2012). For example, based on the results of an experiment, Brewer (2001) pointed out that frames produced either a cognitive or an emotional response. Gross and D’Ambrosio (2004) comparing students’ emotional responses to versions of a newspaper article that emphasized underlying social conditions as the cause of the

1992 Los Angeles riots or emphasized criminality on the part of the rioters, found that frames influenced the emotional responses. Cognitive appraisal models of emotion also posit that frames can change emotional reactions (Gross & D'Ambrosio, 2004).

2.3.1.1. Affective Intelligence Theory (AIT)

Previous research has demonstrated that frames not only change how the audience interprets discussions, they also influence the audience's emotional responses to these discussions (Villanueva, 2021). To explore such kind of associations, I will apply Affective Intelligence Theory (AIT). AIT emerged from the research of neurophysiologists and neuropsychologists (MacKuen et al., 2010). AIT posits that cognitive structures (e.g., frames) influence emotions and emotions in turn are important for people's attentiveness, depth of thought, level of engagement, the development of judgments and behaviors (Choi et al., 2021; Marcus, 2013; Villanueva, 2021). The theory is based on the identification of two neurological subsystems in the brain that affect judgment and behavior, and which are structured by separate emotions (MacKuen et al., 2010; Marcus, 2013).

These two subsystems are the surveillance system (i.e., alarm system) and disposition system (Marcus, 2013). The surveillance system's emotional responses build awareness of the environment against threats (Marcus, 2013), emerging through monitoring the outside environment and being interrupted by habitual actions and focusing attention on what is happening (MacKuen et al., 2010). The surveillance system fosters thinking and information seeking (Marcus, 2013). The disposition system, on the other hand, is connected with the development of behavioral routines (Marcus, 2013; Villanueva, 2021) and individuals' dispositions towards the outside world that governs habitual activities (MacKuen et al., 2010).

Emotions like *aversion* and *enthusiasm* stimulate the disposition system and motivate people to handle relevant information routinely, with less attention given to it (MacKuen et al., 2010). On the other hand, *fear* and *anxiety* influence the surveillance system, urging people to give more attention and effort for thorough processing of information (Choi et al., 2021; MacKuen et al., 2010). Thus, the emotions associated with surveillance system like fear may increase the level of engagement.

This literature review so far illuminated the hypotheses and research model proposed in section 2.5 to examine framing effects in technology setting. Before presenting the research model and hypotheses, I review the literature on technological frames and more specifically AI frames.

2.4. Framing Technology

Different technologies such as nuclear power as in (Gamson & Modigliani, 1989), nanotechnology as in (Lemańczyk, 2013; Şenocak, 2017) and big data as in (Guenduez et al., 2020) were examined in the prior literature on framing technology. For framing technology, a specific concept, *technological frames*, was introduced by Orlikowski and Gash (1994).

Even though frames are generally individually held, technological frames have been studied at the individual, group, organizational, and even industry levels (Davidson & Pai, 2004). For example, technological frames have been researched in the information systems field at the organization level in studies by Davidson (2006); Davidson and Pai (2004); Olesen (2014); Orlikowski and Gash (1994); and J. P. Walsh (1995) and individual level by Guenduez et al.(2020) for exploring what public managers think about big data.

The following section describes technological frames.

2.4.1. Technological Frames

In their paper “Technological Frames: Making Sense of Information Technology in Organizations,” in 1994, Wanda Orlikowski and Debra Gash introduced the concept of *technological frames* to the Information Systems (IS) community, identifying them as,

that subset of members’ organizational frames that concern the assumptions, expectations, and knowledge they use to understand technology in organizations. This includes not only the nature and role of the technology itself, but the specific conditions, applications, and consequences of that technology in particular contexts (p. 178).

Organizational studies have often looked at how frames originate, how they represent the information environment, and how they are employed in managerial sense-making, decision-making, and action (J. P. Walsh, 1995). Starting with representation, Orlikowski and Gash identified three frame domains with which to examine the adoption of a groupware technology in an organization: nature of technology, technology strategy, technology-in-use. Orlikowski and Gash (1994) characterize technology-in-use as the assumptions and expectations about the technology that individuals currently use based on previous technology use experiences. In other words, new technologies’ use depends on the previous knowledge of people about the technologies they currently use (Olesen, 2014).

Technology strategy is identified as the strategy for technology to be used in the future, based on the strategy for current technology use. The final frame domain is technology nature, which is a person’s understanding of how technology is currently used and of how a type of technology may be used in the future. As can be seen in their explanations, these three frame domains are not mutually exclusive categories. In a later study, Spieth et al. (2021) developed a scale consisting of five different but related dimensions of an individual’s technological frame

(personal attitude, application value, organizational influence, industrial influence, and supervisor influence).

Turning to origins, Spieth et al. (2021) pointed out that individuals' education, training, and personal experiences influence the meaning structure concerning technologies, as seen in the example in Orlikowski and Gash (1994). During the process of consultants' first implementation of the technology of Lotus Notes (i.e., a purchased enterprise email system), the consultants shaped their experiences with digital technologies they previously used, such as e-mail and spreadsheets (Orlikowski & Gash, 1994; Spieth et al., 2021). The consultants inferred Lotus Notes as a digital tool appropriate only for individual tasks and neglected its collaboration capacity. Thus, consultants' personal experiences form their meaning structure for new technologies (Spieth et al., 2021).

Finally, considering use, Orlikowski and Gash's (1994) focus was how different groups of organization members (i.e., managers, technologists, and users) made sense of the information technology, more specifically how technology frames differ in these groups and how their interpretations influence their organizational behaviors. They suggested that differences in technological frames of the groups may result in difficulties and unanticipated outcomes during technology implementation. Spieth et al. (2021) investigated the consequences of heterogeneity in technological frames. They examined the relationships between technological frames and two consequences: (1) attitudes towards the technology change and (2) effective commitment to the firm (Spieth et al., 2021).

Orlikowski and Gash also established the concept of technology frames at the individual level but they examined these frames also at the group level by identifying them as shared aspects of individual frames (Davidson & Pai, 2004). This way enables to avoid "the debate

about whether higher-level socio-cognitive structures exist, independent of individual structures” (Davidson & Pai, 2004, p. 476). Thus, according to Orlikowski and Gash, technological frames in groups are like an aggregation of individuals’ cognitive structures constituting the groups. Walsh (1995), however, argued that organizational cognition is “much more than some kind of aggregation or even congregation of individual cognitive processes” (p. 304). In this dissertation, I will also look at the frames at the individual level (the frames in the posts and comments of Redditors).

Gal and Berente (2008) identified several limitations of studies of technological frames. First is the narrow context of previous studies that just examine the frames and their congruence and incongruence. Second, many studies of frames are temporally restricted, because they are only evaluated at one point in time in most previous investigations. Even Orlikowski and Gash’s (1994) original study looked at frames during a 5-month deployment period. Olesen’s (2014) study tackles the problem of temporality by looking at frames four times during a seven-month project. Because frames are dynamic and change throughout time, they must be analyzed at different periods in time (Olesen, 2014).

The third limitation pointed out by Gal and Berente (2008) was that prior studies mostly used interview data to examine frames, which does not fully capture how frames are shaped and changed via social interactions. Olesen’s (2014) study addresses these three limitations by using data from multiple sources such as interviews, data from training sessions, e-mails, discussions, and observation of the subjects using the groupware software individually and in groups to explore how the term of “resistance” is shaped. Through connecting technological frames to user resistance, Olesen (2014) investigated the aspects of arising user resistance.

Many previous publications connect the purpose of framing with various applications, such as the introduction of new technology, processes of interacting with technology, and requirements gathering (Olesen, 2014). Cornelissen and Werner (2014) present a more structured analysis for technology frames as macro, meso, and micro. The researchers consider technological frames under the meso-level frames associated with organizations and point out their importance for the organizations. In a recent study by Spieth et al. (2021), research on technological frames from 1994 to 2020 has been reviewed, and the main points obtained from these studies were presented in a table. I slightly modified their table — I added a more recent study into the last row — and presented it below as Table 2.

Table 2. Research on Technological Frames and related Research on Technological Artefacts (Adapted from Spieth et al., 2021, p. 1967)

| Articles | Measurement of technological frames | Antecedences | Contextual influences | Consequences |
|----------------------------|--|--|-----------------------|--|
| Orlikowski and Gash (1994) | Case-study research: inductive coding of interviews, observations, and archival data | Socially constructed, dimensions of technological frame: <ul style="list-style-type: none"> • Nature of technology • Technology strategy • Technology in use | | <ul style="list-style-type: none"> • Technology development • Technology usage patterns • Technology-induced change |
| Bijker (1995) | Analysis of historical data | Interaction between relevant social groups: <ul style="list-style-type: none"> • Interpretative flexibility • Technological frame closure • Technological frame stabilization | Power conflicts | <ul style="list-style-type: none"> • Technology development • Technology trajectory |
| Davidson (2002) | Case-study research: inductive coding of | Four technological frame domains: | • Formal power | Development and implementation |

| | | | | |
|---------------------------|--|---|--|---|
| | interviews, team meetings, observations, and archival data | <ul style="list-style-type: none"> • IT delivery strategies • IT capabilities and design • Business value of IT • IT-enabled work practices | <ul style="list-style-type: none"> • Informal (interpretative) power | of technologies: reoccurring shifts in frame salience caused repeated reinterpretations of the technological artefact and its requirements Technology implementation |
| McGovern and Hicks (2004) | Case-study research: inductive coding of field notes from, observations, and archival data | Type of partnership <ul style="list-style-type: none"> • Nature of technology • Technology structure • Technology in use | <ul style="list-style-type: none"> • Formal power • Political processes | |
| Allen and Kim (2005) | Thematic content analysis of historical data | <ul style="list-style-type: none"> • Use interpretation • Industry practices • Technology performance | | <ul style="list-style-type: none"> • Technology usage patterns • Technology trajectories |
| Azad and Faraj (2008) | Case-study research: inductive coding of interviews and archival data | <ul style="list-style-type: none"> • Frame differentiation • Frame adaptation • Frame stabilization | <ul style="list-style-type: none"> • Power balance • Internal political behavior • External events | Negotiated truce frame that guides technology implementation |
| Kaplan and Tripsas (2008) | None; conceptual and theoretical | Interactions of: <ul style="list-style-type: none"> • Producers • Users • Institutions | Technology life cycle | Technology trajectories: uncovering intertemporal interactions among multiple actors' framing, collective technological frames, and technology trajectories |
| Mishra and Agarwal (2010) | Cross-sectional survey: three latent constructs; each construct is operationalized using four to six items | Interpretation of technological artefact in terms of a: <ul style="list-style-type: none"> • Benefits frame • Threat frame • Adjustment frame | Organizational capabilities: <ul style="list-style-type: none"> • Technological opportunism • Technological sophistication | Technology usage |

| | | | | |
|-----------------------|---|---|--|--|
| Leonardi (2011) | Case-study research: inductive coding of interviews and archival data | Technology concepts shape frames around cultural resources that guide actors' problem-construction practices | Actors' affiliations with a social group | Cross-functional collaboration in new product development |
| Vaccaro et al. (2011) | Case-study research: inductive coding of interviews, observations, and internal and external archival data | <ul style="list-style-type: none"> • Technological competencies • Strategic objectives • Complementary assets | Granularization of the design space/degree of modularization (e.g., how the design space is divided into components and subcomponents) | Development of knowledge in new product development |
| Furr et al. (2012) | Analyses of panel data: top management team members' expertise operationalized as proxies assessing their industry affiliations and other biographical data | <ul style="list-style-type: none"> • Domain insider • Domain outsider • Complementary | | Degree of technology change in the venture's product portfolio |
| Mazmanian (2013) | Case-study research: inductive coding of interviews, observations, and internal and external archival data | Reframing of technologies: <ul style="list-style-type: none"> • Occupational identity • Materiality • Vulnerability to social pressure • Visibility of communication acts | | Heterogeneity of technology usage patterns within a user group |
| Olesen (2014) | Case-study research: inductive coding of interviews, observations, and internal and external archival data | Social interaction within a group of actors determining the content of a technological frame | Formal power | <ul style="list-style-type: none"> • Technology implementation • Technology usage patterns |

| | | | | |
|---------------------------|---|--|---|---|
| Van Burg et al. (2014) | Case-study research: inductive coding of interviews, historical narratives, and internal and external archival data | Events trigger (re-)framing: Threat Opportunity | <ul style="list-style-type: none"> • Evolving relational context (prior relationships and contractual governance mechanism) • Developing knowledge base (accumulated stock of tacit knowledge and formal appropriability) | Interorganizational knowledge transfer that (intertemporally) can shape the context |
| Young et al. (2016) | Case-study research: inductive coding of interviews, field notes, and internal and external archival data | Inconsistencies and incongruences: Between and within different groups Within the technological frame (nature of technology, technology strategy, and technology in use) | Market, technological, and competitive turbulence Internal reorganization | Technology implementation Technology-induced organizational change |
| Anthony (2018) | None; conceptual and theoretical | Interpretation as: Threat Opportunity | Salience of status differences: the influence of status differences on the interaction of actors | Acceptance or questioning of the technology's output and its effects on the novelty of knowledge outcomes Heterogeneity of the responses to disruptive innovations among actors within an ecosystem |
| Kumaraswamy et al. (2018) | None; conceptual and theoretical | Framing practices of disruptive innovations: Threat Opportunity | | Technology hypes |
| Hoppmann et al. (2020) | Case-study research: inductive coding of interviews, and internal and | Framing dimensions (potential, prospect, performance, progress) | Technology life cycle: <ul style="list-style-type: none"> • Technology maturity • Technology evolution | |

| | | | |
|------------------------|---|--|---|
| | external archival data | Framing tactics (conclusion, conditioning, concession) | |
| Seidel et al. (2020) | None; conceptual and theoretical | Exchange of rumors and propositions among consumers, producers | Development of technologies and new products |
| Benschop et al. (2022) | Case-study research: analysis of 20 business cases for large Dutch government information systems projects with an exploratory mixed-method design, qualitative and quantitative analysis | | Newly proposed information systems are framed more positively, while the existing information systems are framed with more negative adjectives. |

Regarding measurements of technological frames, previous research generally employs thematic content analysis and qualitative analysis to examine individuals' beliefs, interpretations, and understandings (Spieth et al., 2021). These methods usually code the meaning of words, slogans, phrases, and metaphors found in internal and archival data. Qualitative research also examines interview data and archival sources to explore the social interactions that shape technological frames through ethnographic approaches or multiple case studies.

Research can also apply quantitative measures and mixed methods. In a more recent study, Benschop et al. (2022) examined the use of framing in 20 business cases for large Dutch government information systems projects with an exploratory mixed-method design. Their mixed-method included a qualitative, exploratory phase that served as input for a following quantitative analysis (Benschop et al., 2022). In the first phase, Benschop et al. (2022) conducted a linguistic analysis of the language use, in particular, they examined how the adjectives are used

for indicating positive and negative sides of new technology. In the second phase, they conducted a statistical analysis by giving weights to these adjectives and then comparing the weights of the adjectives used when an existing system is depicted versus those used for proposing a new system. Guenduez et al. (2020) analyzing technological frames on the individual level for exploring how public managers interpret *big data*, employed a mixed method, in particular Q-methodology (not included in Table 2). Guenduez et al. (2020) combined qualitative analysis through which he interviewed key informants with quantitative analysis involving principal component analysis (PCA) as steps of Q-methodology.

With respect to antecedents of technological frames and contextual influences of technological frames, previous studies indicate that technological frames are grounded on individuals' experiences, their social affiliations, and their industrial affiliations (Spieth et al., 2021). Individuals' education, training, and personal experiences affect their technological frames (Spieth et al., 2021). Considering possible factors playing role in constructing technological frames, Mishra and Agarwal (2010) and Spieth et al. (2021) investigated them as latent variables, at the organization level and at the individual level respectively. Prior studies also examined inconsistencies and incongruences between and within different groups, whether the power influences inconsistencies and incongruences, how the congruence or lack of congruence, between-group frames have influenced the implementation of technology.

With regards to consequences of technological frames, even if the previous research generally grounded the antecedents of technological frames at the individual level, their consequences on technology development, usage, and implementation are often investigated collectively (Spieth et al., 2021). The variety in individual responses to new digital technologies influences the collective sense-making of that technology. Technological frames serve as

interpretive constructs through which individuals and groups “reduce a technology’s complexity, direct their attention to its focal features, and organize and assign meaning to that technology” (Spieth et al., 2021, p. 1968).

Because an individual’s technological frame constructs their interpretation of the technology, the frame is expected to affect their attitudes towards that technology (Spieth et al., 2021). These attitudes include individuals’ perceptions, reactions, and behavioral changes. When an individual’s interpretation is positive towards a technology, this person tends to recognize the technology’s advantages and be more confident and optimistic about that technology (Spieth et al., 2021). If an individual’s technological frame triggers a positive interpretation of technology (i.e., positive valence), that person perceives the technology as potentially useful (Spieth et al., 2021). Furthermore, frames might manipulate peoples’ decision-making behavior related to technology use or support of its use. For example, Benschop et al.’s (2022) research revealed that newly proposed information systems are framed more positively, while the existing information systems are framed with more negative adjectives. This type of framing could cause a subconscious bias on decision-makers regarding investing in new information systems projects (Benschop et al., 2022).

2.4.1.1. AI Frames

The predominant use of frames for AI has been in analyzing the presentation of the technology in the media. Fast and Horvitz (2017) examined how AI is discussed in the articles published by the New York Times over a 30-year period (more than 3 million articles in total) and how these discussions changed over this period. They did not use the term *frame* explicitly, but their discussion of “measures” is similar conceptually. Fast and Horvitz (2017) separated the measures into three categories: general measures such as engagement and optimism vs. pessimism; hope

for AI measures as the impact on work (positive), education, transportation, healthcare, decision making, entertainment, singularity (positive), and merging of human and AI (positive); concerns for AI measures as loss of control, impact on work (negative), military applications, absence of appropriate ethics, lack of progress, singularity (negative), merging of human and AI (negative). Fast and Horvitz (2017) found that discussions of AI have increased steeply since 2009 and that these discussions have been more optimistic than pessimistic. Nevertheless, they found that worries about loss of control of AI, ethical concerns for AI, and the negative impact of AI on work were common in recent years. They also found that hopes for AI in healthcare and education have grown over time. Duberry and Hamidi (2021) analyzed AI and COVID 19 by adopting Fast and Horvitz's (2017) measures as topics under the Risk and Benefit frame (omitting the "transportation" (benefit) and "military applications" (risk) categories).

Chuan et al. (2019) explored how AI was framed in U.S. newspapers through a content analysis grounded on framing theory. More specifically, this paper demonstrates the dominant topics and frames, and the risks and benefits of AI stated in five main American newspapers from 2009 to 2018. The frames for AI presented by Chuan et al. (2019) are risk and benefit framing, societal versus personal impact framing, and thematic versus episodic issue framing. The topics are technology development and application, business and economy, politics and policy, ethics, threat, science fiction, entertainment, and education. Their findings pointed out that business and technology are the most covered topics in the news of AI. The benefits of AI are mentioned more frequently than its risks, but risks of AI are often mentioned with greater specificity (Chuan et al., 2019).

I list previous AI frames identified in prior research in Table 3.

Table 3. AI-related Technological Frames based on the Existing Literature

| Frame | Meaning |
|---|--|
| Benefit | |
| 1. Impact on work (positive) | “AI makes human work easier or frees us from needing to work at all” (Fast & Horvitz, 2017, p. 964). |
| 2. Improving human well-being | AI helps to improve human life and well-being (Chuan et al., 2019). |
| 3. Reducing human bias and social inequality | AI helps to reduce human bias and social inequality (Chuan et al., 2019). |
| 4. Impact on education (positive) | “AI improves how students learn, e.g., through automatic tutoring or grading, or providing other kinds of personalized analytics” (Fast & Horvitz, 2017, p. 964). |
| 5. Impact on transportation (positive) | “AI enables new forms of transportation, e.g., self-driving cars, or advanced space travel” (Fast & Horvitz, 2017, p. 964) or offers some advantages. |
| 6. Impact on entertainment (positive) | “AI brings us joy through entertainment, e.g., though smarter enemies in video games” (Fast & Horvitz, 2017, p. 964). |
| 7. Impact on decision-making (positive) | “AI or expert systems help us make better decisions, e.g., when to take a meeting, or case-based reasoning for business executives” (Fast & Horvitz, 2017, p. 964). |
| 8. Impact on healthcare (positive) | “AI enhances the health and well-being of people, e.g., by assisting with diagnosis, drug discovery, or enabling personalized medicine” (Fast & Horvitz, 2017, p. 964). |
| 9. Singularity (positive) “Singularity is the point where AI and machine learning using AI begins to exceed the capability of humans” (Harlow, 2019, p. 393) | “A potential singularity will bring positive benefits to humanity, e.g., immortality” (Fast & Horvitz, 2017, p. 964). |
| 10. Merging of human and AI (positive) | “Humans merge with AI in a positive way, e.g., robotic limbs for the disabled, positive discussions about the potential rise of transhumanism” (Fast & Horvitz, 2017, p. 964). |
| Risk/Harm/Loss | |
| 11. Loss of control | “Humans lose control of powerful AI systems, e.g., Skynet or “Ex Machina” scenarios” (Fast & Horvitz, 2017, p. 964). |
| 12. Impact on work (negative, e.g., loss of jobs) | “AI displaces human jobs, e.g., a large-scale loss of jobs by blue-collar workers” (Fast & Horvitz, 2017, p. 964). |
| 13. Absence of Appropriate Ethics (embedded bias, privacy) | “AI lacks ethical reasoning, leading to negative outcomes, e.g., loss of human life” (Fast & Horvitz, 2017, p. 964). |

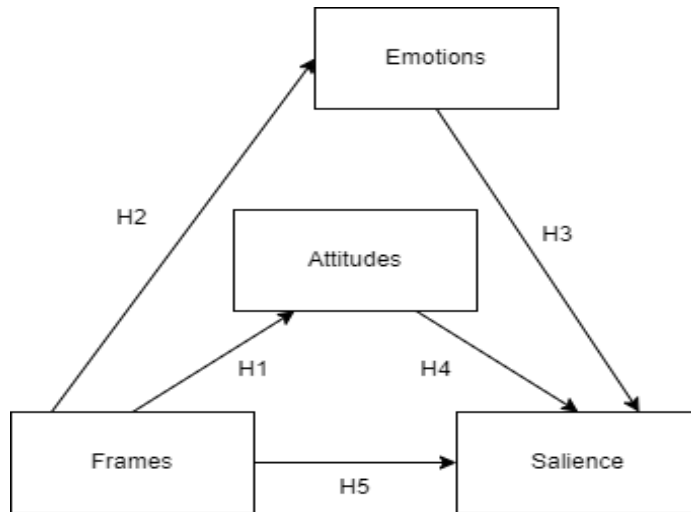
| | |
|--|--|
| concern, misuse, Pandora’s Box (unforeseeable risk) | |
| 14. Lack of progress (shortcomings of AI) | “The field of AI is advancing more slowly than expected, e.g., unmet expectations like those that led to an AI Winter” (Fast & Horvitz, 2017, p. 964). |
| 15. Military applications | “AI kills people or leads to instabilities and warfare through military applications, e.g., robotic soldiers, killer drones” (Fast & Horvitz, 2017, p. 964). |
| 16. Singularity (negative) | “The singularity harms humanity, e.g., humans are replaced or killed” (Fast & Horvitz, 2017, p. 964). |
| 17. Merging of human and AI (negative) | “Humans merge with AI in a negative way, e.g., cyborg soldiers” (Fast & Horvitz, 2017, p. 964). |

However, research on AI framing so far has not yet examined its connections to emotions, attitudes, and behaviors. This dissertation examines whether AI frames create social influence as in frames in general depicted in section 2.3 through looking at possible effects of AI frames in post titles on emotional and attitudinal responses and commenting behavior. Section 2.5 presents the research model and hypotheses.

2.5. Research Model and Hypotheses

Lazarus (1991) suggests *cognition*, *emotion*, and *motivation* as three harmonically integrated constructs of mind, and *behaviors towards the environment* is connected to the mind. As parallel to these constructs, synthesizing prior literature including AIT and framing theory, I propose an integrated model (illustrated in Figure 1) comprising the components of *frames*, *emotions*, *attitudes*, and *salience* of the posts (measured by the *number of comments* due to its association with the level of engagement) for the purpose of exploring potential *social influence* on Reddit in the technology context and assess the proposed hypotheses.

Figure 1. Research Model



For developing the research hypotheses, I drew upon the prior literature on framing and its relationships with emotions, attitudes, and the level of engagement. AI frames were summarized in Table 4 under the comprehensive frames: *benefit, risk and harm*, and include them in the hypotheses. In addition to these three frames, I also included *loss* frame referring to job losses stemming from AI automation inspired by Plutchik’s psychoevolutionary theory’s components stated in Table 1 because it was connected to “loss of valued object” as similar to “loss.”

As an individual’s technological frames shape their perception of the technology, frames are expected to affect their attitudes towards that technology (Spieth et al., 2021). For example, if a person’s frames are associated with other positive concepts, this person tends to recognize that technology’s advantages and be more confident and optimistic about that technology (Spieth et al., 2021). As this dissertation focuses on AI frames, possible relationships between AI frames in posts’ titles and attitudes appeared in the corresponding comments were examined.

The first set of hypotheses are:

H1-1. Comments on posts using a harm frame are more likely to display a negative sentiment than a positive sentiment.

H1-2. Comments on posts using a risk frame are more likely to display a negative sentiment than a positive sentiment.

H1-3. Comments on posts using a benefit frame are more likely to display a positive sentiment than a negative sentiment.

H1-4. Comments on posts using a loss frame are more likely to display a negative sentiment than a positive sentiment.

Changes in attitudes and behaviors stemming from discrete emotions (e.g., *anger*, *fear*) have been studied by cognition-emotion-behavior related research (e.g., Lazarus, 1991, 2006; Plutchik, 1980, 2000). AIT also highlights the relationships of these neurological subsystems with discrete emotions. Emotional responses to news through the lens of AIT have mainly been researched in political literature, including Lee and Choi (2018) and Marcus et al. (2019). Marcus et al. (2019) examined specific emotional responses on elections that occurred in the periods of grown threat, such as two 2015 terror attacks in France.

Marcus et al. (2019) found that threats can produce both *anger* and *fear*. Although previous studies applying AIT were generally in a political setting, AIT may be applied on research in different settings (Lee and Choi, 2018). For example, emotional responses to news associated with other situations such as news about terrorism or natural disasters linked to threats or harm can be researched through the lens of AIT (Lee and Choi, 2018). These kinds of representation of news stories in varied domains such as terrorism and natural disasters might stimulate people's negative emotions such as *fear* or *anxiety* (Lee and Choi, 2018).

Apart from AIT, previous research such as Lazarus (1991) and Plutchik (1980) had reviewed in detail other discrete emotions like *joy* and *sadness*. Lazarus (1991) deemed *happiness* and *joy* as almost the same and connected it with varied circumstances such as "...a new car; the love of a good woman (man); engaging in productive work; getting what one wants" (p. 265) as analogous to Plutchik's (2000) association of *joy* with "gain of valued object" (p. 69). On the other hand, *sadness* was characterized by Lazarus (1991) as "the amount of unpleasant affect and lowered mood related to the exposure to suffering, disappointment, and object loss" (p. 322) as parallel to Plutchik (2000) associating *sadness* with "loss of valued object" (p. 69).

Since the phenomena (e.g., threats or gain/loss of valued object) are also connected with future interpretations concerning technology, I analyze the emotions of *fear*, *anger*, *joy*, and *sadness*. Adapting this literature synthesis above involving in AIT and especially Plutchik's (1980, 2000) deduction of key elements in the emotion sequence depicted in Table 1 to technology setting, I test whether such emotional connections exist in AI-related conversations proposing the second set of hypotheses as:

H2-1. Comments on posts using a harm frame are more likely to display anger.

H2-2. Comments on posts using a risk frame are more likely to display fear.

H2-3. Comments on posts using a benefit frame are more likely to display joy.

H2-4. Comments on posts using a loss frame are more likely to display sadness.

Lee and Choi (2018) investigated how social views on presidential debates related to emotions (anger, fear, and enthusiasm) and how these relationships influence engagement and tolerance for opposite views. They conducted a national survey related to the 2017 presidential election. The research findings demonstrated that social views on presidential debates prompt fear and enthusiasm; enthusiasm influences cognitive elaboration; and cognitive elaboration positively influences tolerance for opposing views (Lee and Choi, 2018).

Choi et al. (2021) investigated the relationship between emotions and engagements analyzing 12,179 news stories posted on the four U.S. newspapers' Facebook pages. They looked at the influences of emotions on user engagements on posts in different settings such as politics, nation, economy, international, culture, opinion, and technology through AIT. They examined six discrete emotions (sadness, anger, fear, disgust, happiness, and contempt) seen in visual news stories, the positiveness of news text, and how they are related to the activities of sharing news, commenting on them, and reacting with them. Choi et al. (2021) considered these activities as indicators of user engagements. They found that “users are less likely to share or comment on news posts that convey positive emotions, although they tend to react to such news frequently. The most prominent kind of emotion associated with user engagement activities was “sadness”” (Choi et al., 2021, p. 1018).

On the other hand, Entman (1993) links framing theory with *salience*: “to frame is to select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation for the item described” (p. 52). Entman (1993) defines *salience* as “making a piece of information more noticeable, meaningful, or memorable to audiences” (p. 53). If a post is more salient, namely it is more noticeable, thus *the level of engagement* is expected to be higher. Relating this back to Choi et al.'s (2021) commenting-engagement connection, and Venkatesan and Valecha's (2021) social influence measurement based on the number of retweets, the proposed research model also includes the variable of *salience* to be measured by the *number of comments*.

Drawing on this literature synthesis, I propose the third set of hypotheses as:

H3-1. The emotion of *anger* in posts is positively related to salience of the technology-related posts.

H3-2. The emotion of *fear* in posts is positively related to salience of the technology-related posts.

H3-3. The emotion of *joy* in posts is negatively related to salience of the technology-related posts.

H3-4. The emotion of *sadness* in posts is positively related to salience of the technology-related posts.

AIT illustrates that negative news increase the level of engagement, while positive perceptions of news decrease it (Choi et al., 2021). Another research study also illustrated that articles reflecting positivity tended to decrease the level of engagement and have fewer user comments (Diakopoulos & Naaman, 2011). Thus, I propose the fourth set of hypotheses as:

H4-1. Positive sentiment in posts is negatively related to the salience of the technology-related posts.

H4-2. Negative sentiment in posts is positively related to the salience of the technology-related posts.

Inspiring Plutchik's (1980, 2000) theory that displays key elements of an emotion sequence and adapting it to technology setting through benefitting from this literature synthesis, I develop the hypotheses proposed in this dissertation. Table 4 presents a summary of the combination of this literature synthesis that reveals the proposed hypotheses with possible relevant perceived technology impacts (stimulus). The first and third columns are the same as the first four rows of the first and third columns of the Table 1 depicting Plutchik's (1980, 2000) key elements of emotion sequence. I chose those four rows because perceived AI impacts seen in the literature mostly involve threats, obstacles, some gains, and some losses like loss of jobs.

The second column was based on the comprehensive frames (i.e., risk, harm, and benefit) stated in Table 4 demonstrating AI frames the prior relevant literature revealed. Additionally, loss frame was added like in the fourth row of Table 1 since loss of valued object could be connected to loss of jobs, which could be connected to loss of valued object perception as in

Plutchik’s emotion sequence. The fourth and fifth columns were generated based on the literature synthesis explained above.

Table 4. Social Influence Sequence in Technology-related conversations

| Perceived Technology Impact (Stimulus) | Perceived Technological Frame | Emotion | Attitude | Saliency of the posts |
|--|-------------------------------|---------|----------|-----------------------|
| Threat | “Risk” | Fear | Negative | More |
| Obstacle | “Harm” | Anger | Negative | More |
| Gain of valued object | “Benefit” | Joy | Positive | Less |
| Loss of valued object | “Loss” | Sadness | Negative | More |

Finally, a frame embedded in a post that increases saliency based on the framing theory, thus increasing another person’s attention and motivation reading this post to engage in conversation, which may be a driver of social influence. To examine this relationship, considering the frames specified in Table 4, I propose the fifth set of hypotheses as:

- H5-1.** Posts using a *harm* frame have higher saliency.
- H5-2.** Posts using a *risk* frame have higher saliency.
- H5-3.** Posts using a *benefit* frame have lower saliency.
- H5-4.** Posts using a *loss* frame have higher saliency.

CHAPTER 3. METHODOLOGY

3.1. Introduction

This chapter describes the process that integrates experiences derived from a pilot study to guide the design of the main dissertation work that consists of three main studies. Specifically, this chapter depicts how I chose the subreddits as the sites for this dissertation's inquiry, how I collected data, and how I analyzed this data implementing a mixed-methods approach on which quantitative aspect is dominant even if it includes also qualitative pieces. That is, it comprises mostly quantitative tools such as unsupervised topic modelling supported by human judgment to be active at the stage of labelling frames (this part could be recognized as qualitative), open pretrained models (Dalgali & Crowston, 2019) fine tuned for this work to be operational at the stage of detecting categories of emotions and attitudes, and statistical analyses to investigate possible relationships posed in the research model (see Figure 1).

Quantitative research methods comprise non-experimental research and experimental research methods (Hussain et al., 2019). Non-experimental research or descriptive research methods analyze research variables in their nature form without any changes and include three main categories: observational research method, archival data research method, and survey research method (Hussain et al., 2019).

As social media data built by users' conversations is transferred from the past through today, this data can be considered as conversations' records, namely as archived data. Moreover, we observe emotions, attitudes, and behaviors in these social media conversations. This work employs observation research method through analyzing archived data. Thus, this study may be considered as a combination of observational research method with archival data research method.

3.2. Research Site: Reddit

To obtain public feelings, although surveys and interviews are commonly used, the questions in these methods are designed based on only the researchers' preferences, and the answers depend on the respondents' understandings of questions, which could be a limitation. Social media data, however, are produced by the users freely, thus natural; many people prefer to be involved in social media discussions to share their ideas, and hence the data are growing as long as users post and comment, which makes social media data organic (Chen & Tomblin, 2021). Social media data usage, therefore, has been increasing in various types of research work to explore public perceptions as in Hristova and Netov (2022) and public attitudes as in Mahor and Manjhvar (2022); Sai Kumar et al.(2021), and revealed important and informative findings, thus this proposed study also follows an analogous approach.

Social media is an ICT that allows natural real-time discussions among the public; as well as a potent media service for documenting events while they are occurring (Venkatesan & Valecha, 2021), which conveys data from the past to today and from today to the future. Although ICT research related to social media predominantly utilizes Twitter, in recent years Reddit has gained scholars' attention and it has been harnessed as a data source in research studies, as in (Kitchens et al., 2020; Chen & Tomblin, 2021; Villanueva, 2021; Öcal et al., 2021). Twitter has been widely used for academic study since tweets are deemed as "public," (Proferes et al., 2021) with open APIs and with the users regularly responding to current events, creating a useful place to obtain observational data (Proferes et al., 2021). Reddit has been satisfying many of these same standards, moreover, it offers the following additional advantages.

Reddit itself is a huge community consisting of thousands of smaller communities; these sub-communities within Reddit are called "subreddits," each of which centers on different topics,

in which users share their interests, thoughts on relevant content. This opportunity strikes many researchers to utilize Reddit data since they can access a large amount of data on various topics already created by Reddit users and can select relevant subreddits as their samples to answer their research questions. Moreover, Reddit posts often depend on news obtained from traditional media (Villanueva, 2021), and other valuable external sources such as experts' context-related videos (Öcal et al., 2021). Further, Reddit provides its users the opportunity to self-select their communities and as many as they want.

As an additional advantage, users benefit from a level of anonymity on Reddit not typically accomplished on other social media platforms, thus users may feel more secure and share more honest thoughts on a topic. Also, as the data are public and pseudonymous (users' names are not their real names), research analyzing Reddit data is often exempted from institutional ethics review. Due to a variety of advantages, Reddit data usage has been rapidly increasing in the past decade and much of that analysis has been conducted in computer science and related disciplines using computational methods (Proferes et al., 2021).

Reddit involves over 50 million daily active users, 100 thousand active communities, and 13 billion posts and comments¹ (as of February 26, 2022). Since participation on Reddit is pseudonymous, collecting demographic information about Redditors is quite difficult (Proferes et al., 2021). However, in 2021, Reddit's site administrators reported that a majority (58%) of users were between 18 and 34 years old and were male (57%).

In this dissertation, the purpose was discerning general frames, emotions, and attitudes about the future of AI in text data. In addition, looking at the relationships among these constructs to examine possible social influence drivers in social media. Social influence

¹ <https://www.redditinc.com/>

describes how thoughts, emotions, attitudes, and behaviors respond to those of others in their social environment. Reddit enables me to choose relevant subreddits (e.g., Futurology) and to obtain emotional, attitudinal responses because comments are responses to posts, Reddit is the research setting of this dissertation.

3.2.1. Selection of Subreddits

I chose relevant subreddits on the grounds of my research purposes. The priority in subreddit selection process was capturing the subreddits that mainly discuss about the future trends around AI. Thus, first I conducted an artificial intelligence (AI)-related keyword search with the purpose of identifying where the future of AI-related conversations is taking place. This keyword search process ended up a selection of fifteen subreddits illustrated in Table 5 given their inclusion of the future of AI-related posts and their descriptions. Particularly, I selected these subreddits because they are: (1) explicitly devoted to the future trends and speculations (i.e., Futurology, tomorrowsworld, DarkFuturology, conspiracy), (2) particularly focus on AI (i.e., ArtificialIntelligence, artificial, agi, MachineLearning, deeplearning, Automate, singularity), and (3) dedicated to the news and discussions about technology, science around the world that also include varied contemporary AI-related conversations (i.e., worldnews, science, tech, technology).

Table 5. Information about Subreddits

| Subreddit | Description of Subreddit ² | Number of Members |
|----------------|--|-------------------|
| Futurology | A subreddit devoted to the field of Future(s) Studies and speculation about the development of humanity, technology, and civilization. | 15.6m |
| tomorrowsworld | A subreddit for the future of the world conversations | 816 |
| DarkFuturology | A subreddit for dystopian trends. | 68.1k |

² These descriptions were extracted from the subreddit, slightly edited or shortened for presentation.

| | | |
|------------------------|---|-------|
| conspiracy | The conspiracy subreddit is a thinking ground. Above all else, we respect everyone’s opinions and ALL religious beliefs and creeds. We hope to challenge issues that have captured the public’s imagination, from JFK and UFOs to 9/11. This is a forum for free-thinking, not hate speech. | 1.7m |
| ArtificialIntelligence | A subreddit for Artificial Intelligence conversations | 78.1k |
| artificial | A subreddit for Artificial Intelligence conversations | 153k |
| agi | A subreddit for Artificial general intelligence (AGI) conversations, which is also referred to as “strong AI”, “full AI” or as the ability of a machine to perform “general intelligent action.” | 12.1k |
| MachineLearning | A subreddit for Machine Learning conversations | 2.5m |
| deeplearning | A subreddit for Deep Learning conversations | 80.2k |
| tech | A subreddit dedicated to the news and discussions about the creation and use of technology and its surrounding issues. | 11.4m |
| technology | Subreddit dedicated to the news and discussions about the creation and use of technology and its surrounding issues. | 12.2m |
| worldnews | A place for major news from around the world, excluding US-internal news. | 29.1m |
| science | This community is a place to share and discuss new scientific research. Read about the latest advances in astronomy, biology, medicine, physics, social science, and more. Find and submit new publications and popular science coverage of current research. | 27.7m |
| Automate | A place for the discussion of automation, additive manufacturing, robotics, AI, and all the other tools we’ve created to enable a global paradise free of menial labor. All can share in our achievements in a world where food is produced, water is purified, and housing is constructed by machines. | 47.1k |
| singularity | Everything pertaining to the technological singularity and related topics, e.g., AI, human enhancement, etc. | 150k |

3.3. Data Collection and Cleaning

For harvesting data from the selected subreddits, I use the Reddit API through PRAW – Python Reddit API Wrapper – to gather posts and comments. I fetch all the posts that include the terms “Artificial intelligence”, “AI”, “artificial intelligence”, “Artificial Intelligence” from the chosen

subreddits, without any time constraints, and all the comments corresponding to the extracted posts. I extracted top level comments to be responses directly to posts, and each post includes at least one comment to examine the relationships between posts and their corresponding comments for exploring potential social influence.

After extracting data, I realized some rows in comments were “deleted” or “removed,” and some comments were expressions “please reply to OP’s comment here:” and “the following submission statement was provided by...” These rows were removed from the data as they do not reflect contributions to the discussion. I did not do further data cleaning because I intend to protect natural structures of post titles and comments to fit better in BERT models.

This data cleaning process yielded 998 unique post titles and their corresponding comments, a total of 16611 comments, thereby the number of the total of unique post titles and comments is 17609. The posts were created between 2/19/2013 and 7/3/2022 by 671 unique users. The distribution of the posts and the comments by years and subreddits is depicted in Figure 2 and Figure 3, respectively.

The cleaned data (post titles and comments) were then analyzed to identify frames and to classify different emotions and sentiments. Instead of the text bodies of the posts, I analyzed the titles of posts since many posts’ main bodies were not rich text data, but rather videos, images, or a link for another source. However, each post has a title that reflects the main idea of the post. Chase and Qiu (2017) also found that Reddit post titles successfully represent the main points of Reddit submissions and their work centers on semantic analysis of Reddit post titles. For comments on posts, however, I directly analyze the body of comments since each comment itself includes rich text data.

Figure 2. The Number of Posts by Years and Subreddits

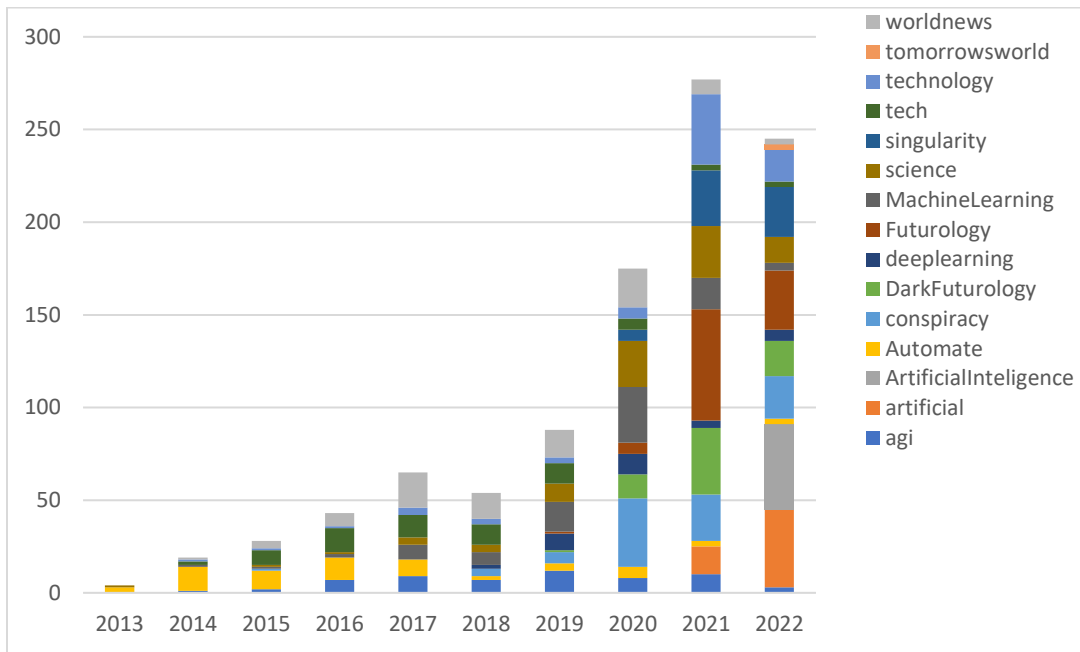
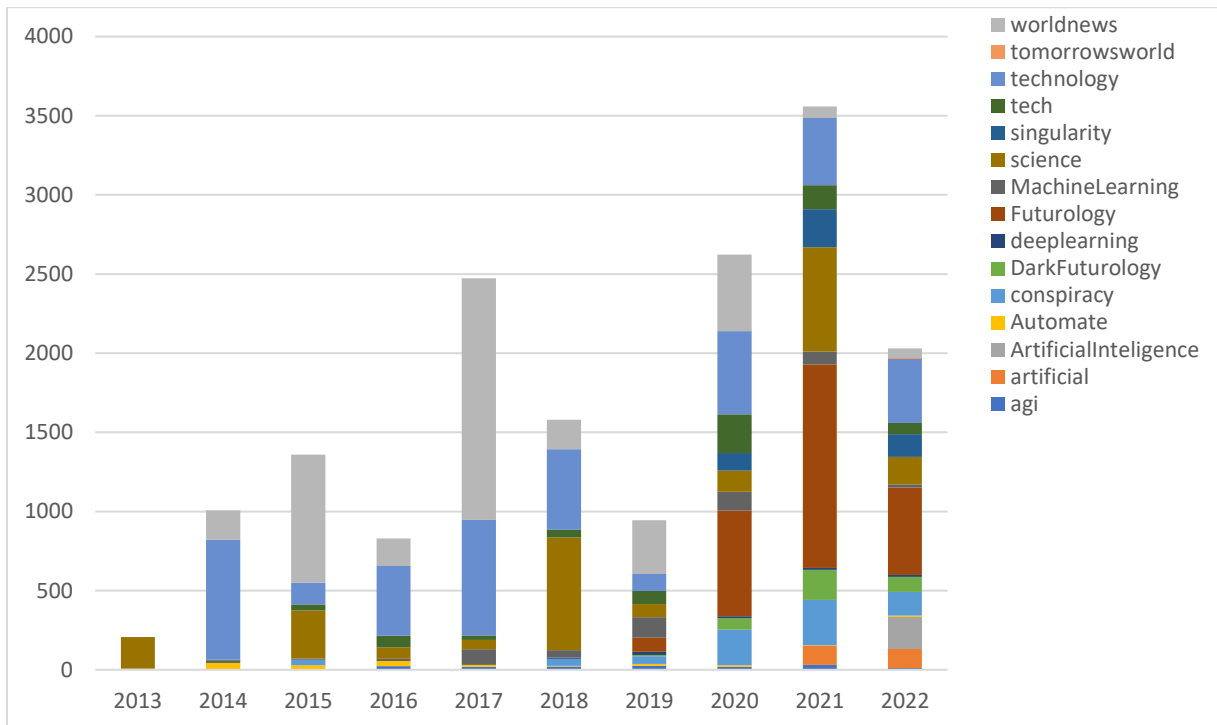


Figure 3. The Number of Comments by Years and Subreddits



3.4. Data Analysis

The data analysis process followed in this dissertation is a consolidation of topic modelling to identify frames, text classification to explore emotions and attitudes in text data, and statistical analyses to probe associations of these variables.

3.4.1. Frame Identification

In the subsequent section, I review the prior frame identification methods.

3.4.1.1. Methods Used in the Literature to Identify Frames

For identifying frames, a deductive strategy is generally used, in which researchers search for a limited number of frames that are predefined in the literature (Walter & Ophir, 2019). For example, Villanueva (2021) conducted a content analysis to investigate climate-change frames through a deductive approach in which the frames used in the codebook were pre-defined in the literature. Yet, the adaptation of frames determined in the prior literature may not be adequate to cover the frames in the new corpora or may limit the lenses through which coverage should be analyzed in the new corpora. Thus, such a method may lead researchers to only identify the frames they were consciously searching for (Walter & Ophir, 2019).

These disadvantages triggered researchers to develop inductive methods for finding frames (Walter & Ophir, 2019). One inductive method used for frame identification is content analysis with open coding, in other words, open coding of documents without depending on predetermined coding tools. Farrington (2020), for instance, conducted an inductive coding to explore frames in Twitter that show reactions of a segment of the public to an advertisement. In addition to using the two approaches separately, some scholars benefit from the combination of deductive and inductive approaches. For example, Seay (2021) identified frames about the

Cambridge Analytica-Facebook Scandal in U.S. and U.K. newspapers based on a combined coding book that involves the deductive and inductive categories.

In addition to manual deductive and inductive approaches, computational methods have also been utilized to explore frames. Supervised, unsupervised and mixed computational approaches have been applied for framing analysis. In supervised approach, scholars develop manually annotated frame code schemes or frame corpus that appeal to particular issues such as policy or gun violence, as in Policy frame code scheme by Boydston et al. (2013) and Gun violence frame annotated corpus by Liu et al. (2019) or utilize existing frame corpora (e.g., FrameNet corpus as in Isaeva et al., 2021)) whereby they build classification algorithms to detect frames. Venkatesan and Valecha (2021) applied classification algorithms like random forest and decision trees after manual coding (of potential pre-determined frames what, how, where, and who that characterize social protest activities) to identify the framing of the Egyptian uprising on Twitter. Yet, supervised method is limited as it solely investigates existence of potential pre-determined frames on new corpora, which constrained the contribution of the research.

Recently researchers have also implemented unsupervised (e.g., topic modelling, clustering) and mixed (e.g., combining two methods such as topic modelling with network analysis as in Walter and Ophir (2019)) computational framing analysis methods. For example, Sheshadri et al. (2021) examined framing changes in topical news by the LDA topic modelling approach. The researchers prepared a data set comprising over 12,000 articles from seven news domains and used LDA to detect frame changes. To explore this change, they used a probability distribution of adjectives according to the frequency of their occurrence in data sets (Sheshadri et al., 2021). Dalwadi (2020); Gritsenko et al. (2021); Pavlova and Berkers (2022); Reyes (2019); Wöber (2015) and Ylä-Anttila et al. (2021) also applied topic modelling for frame detection.

Previous research has applied different methods for identifying *AI frames*. The first salient method was content analysis, as in Chuan et al. (2019) and Duberry and Hamidi (2021). Chuan et al. (2019) employed a deductive strategy approach, specifically a deductive content analysis on the grounds of the frames stated in the previous literature. Through this deductive content analysis, Chuan et al. (2019) analyzed AI-related frames and topics in five main American newspapers between 2009 and 2018. Duberry and Hamidi (2021) also applied the deductive content analysis method to identify AI-related frames based on categories, such as benefits and risks, hopes and concerns obtained from the literature.

The AI frames investigated in these two papers were gathered from Fast and Horvitz (2017) who had 8000 AI-related paragraphs annotated by Amazon Mechanical Turk (AMT) workers. First, Fast and Horvitz (2017) gathered annotations for attitudes about the future of AI (from pessimistic to optimistic) on a 5-point Likert scale. Second, specific hopes (e.g., positive impact on work) and concerns (e.g., loss of job) were determined based on finer level annotations. These specific hopes and concerns were presented in this dissertation in Table 1 as well. Third, binary labels for whether hope or concern exists in the paragraph were found by AMT workers. These annotations form their ground truth to classify new paragraphs based on paragraphs' hope or concern inclusion. However, this classification method is limited to only specific frames determined by AMT workers' annotations. If this classification method is applied in other datasets, it would be again constrained with only these frames, which decreases reusability of this method in other data sets. Thus, I utilize topic modelling for exploring AI frames.

Topic Modelling

More recently, topic modelling has become a common machine learning method among computational scholars (Walter & Ophir, 2019). Topic modelling “is a text mining technique which automatically discovers the hidden themes from given documents” (Islam, 2019, p. 1).

Topic modelling has been applied for identifying frames in a text (Walter & Ophir, 2019). Ylä-Anttila et al. (2021) applying topic modelling for frame detection claimed that the concept of *the topic* in *topic modelling* does not indicate a specific feature of the algorithm; the algorithm only knows the clusters of co-occurrences of keywords depending on the collection of textual data like documents. Frames reflect individuals’ perceptions, interpretations, beliefs, assumptions, and expectations, articulated through language, visual images, metaphors, and stories (Orlikowski & Gash, 1994). Entman (1993) highlighted the main functions of frames as “define problems”, “diagnose causes”, “make moral judgments” and “suggest remedies” (Ylä-Anttila et al., 2021, p. 6).

On the other hand, Nisbet (2009) pointed out two important characteristics of frames: First, individuals may discuss the same topic that signifies an overlap of cognitive categories and content in their minds from different aspects within a frame (Nisbet, 2009). Second, “the latent meaning(s) of any frame can be translated instantaneously through frame devices such as catchphrases, metaphors, sound bites, graphics, and allusions to history, culture, and/or literature” (Nisbet, 2009, p. 45).

Ylä-Anttila et al. (2021) claim that when conducting topic modelling if we know all the texts are about a particular topic (as in here the future of Artificial Intelligence), topic modelling “outputs are best interpreted as traces of different ways of discussing a topic – that is, frames” (Ylä-Anttila et al., 2021, p. 5). A variety of posts and comments about the same topic often reflect various perceptions (Liu et al., 2019); for example, a post expressed about the future of AI

may emphasize human-AI collaboration in a positive way through referring to the frame of *benefits* while another post may highlight potential problems like the risk of *loss of control*.

Frames are flexible in structure and content and expected to be shared by other individuals if there is an overlap of cognitive categories and content (Orlikowski & Gash, 1994). Erving Goffman, one of the earliest framing scholars, suggested that words are prompts that allow individuals convey their interpretations, beliefs, assumptions, and expectations through the lens of existing world views (Nisbet, 2009). Thus, word clusters can be helpful for frame identification (Ylä-Anttila et al., 2021). Taking into this consideration and following scholars benefitting from topic modelling to identify frames like Heidenreich et al. (2019), Ylä-Anttila et al. (2021) and Guo et al. (2022), we utilized topic modelling, found word clusters and determined the relevant ones to be AI frames based on the frame characteristics described above.

Different topic modelling techniques and their comparisons based on data analysis are handled in the prior work. For example, Islam (2019) employed three different topic model algorithms as Latent Semantic Analysis (LSA), Non-negative Matrix Factorization (NMF), and Latent Dirichlet Allocation (LDA) to explore the topics of a large number of tweets and found that LDA results outperformed the former two algorithms.

Egger and Yu (2022), on the other hand, indicated the potency of BERTopic comparing it to LDA, NMF and Top2Vec topic modelling techniques, in analyzing tweets. This indication led me to analyze posts and comments harnessing BERTopic. In the following sections, I elucidate two topic modelling approaches, namely LDA and BERTopic, since the first approach is the most wide-ranging traditional topic modelling method (Egger & Yu, 2022) and the latter will be applied in this study.

LDA (Latent Dirichlet Allocation) topic modelling. LDA topic modelling is an unsupervised text analysis approach that is utilized for finding groups of words that characterize the given documents. This approach was introduced by Blei et al. (2003), depicting it as a probabilistic model for collecting discrete data like text corpora. In LDA topic modelling, each document in the corpora is modeled as a combination of a collection of topics probabilities and each topic is modeled as a mixture of a set of word occurrence probabilities. This method expands classical natural language processing methods such as the unigram model and Latent Semantic Analysis (Grün & Hornik, 2011).

This technique is different from the term frequency models since it is mixed-membership modelling (Grün & Hornik, 2011). In the unigram model, each word is illustrated from the same term distribution, and each word in a document is illustrated from the term distribution of the topic (Grün & Hornik, 2011). In mixed-membership models, however, documents are expected to belong to several topics, and the topic distributions that differ based on documents (Grün & Hornik, 2011).

As observed in the pilot study, several limitations of LDA topic modelling method have been drawn attention. First, it neglects semantic relations among words (Egger & Yu, 2022) since the method focuses on word occurrence probabilities. Second, it requires manually determining hyperparameters such as *number of topics (k)*. These determinations complicate topic modelling processes and affect the quality of the model. Moreover, LDA does not allow uncorrelated topics because it is based on frequencies of the common occurrence of words-topics probabilities. Finally, it requires word-document matrices before running topic modelling, which takes additional time and human effort.

With latest advancements in the NLP field, novel topic modelling techniques have been emerged such as Corex, Top2Vec, and BERTopic (Egger & Yu, 2022). BERTopic to be described in the subsequent section mainly addresses these limitations of LDA topic modelling and offers more advanced functions such as search functions (e.g., searching topics associated with a specific word, easily going from topic to documents), hierarchical and dynamic topic modelling.

BERTopic. BERTopic is a model that bolsters clustering methods through a class-based variation of TF-IDF to produce coherent topic representations (Grootendorst, 2022). Grootendorst (2022) describes three stages through which BERTopic produces topic representations. In the first stage, each document is transformed to its embeddings by utilizing a pre-trained language model. Next, the dimensionality of these embeddings is reduced to optimize the process of clustering these embeddings. In the last stage, from these clusters, topic representations are obtained utilizing a custom class-based variation of TF-IDF (Grootendorst, 2022).

3.4.2. Discerning Emotions and Attitudes

The second study aims to discern emotions and attitudes in text, namely in AI-related Reddit conversations. The following section summarizes several computational text analysis methods for emotion and attitude detection and describes the method I am employing.

3.4.2.1. Methods Used in the Literature to Detect Emotions and Attitudes

Recent progress of advanced and varied computational methods and ease of access to massive amount of text data have prompted researchers to discern emotions and attitudes in text utilizing various computational methods. Varied practical open-source software sentiment analysis tools serve researchers. For example, *R syuzhet package* is a dictionary-based approach that can detect

eight emotions (i.e., anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) on large volume of text data utilizing only a few lines of R codes. Yet, negation (e.g., “we **don’t** need to fear AI”) is not addressed by this package.

An R package handling negation, *R sentimentr package*, was released to generate sentiment polarity of text; namely positivity or negativity, but it does not reveal discrete emotions like fear. Python packages such as VADER and TextBlob are other popular dictionary-based easily operated open-source sentiment analysis tools that explore polarity.

Linguistic Inquiry and Word Count (LIWC) is another wide-ranging method to analyze emotions and attitudes in text (Villanueva, 2021). “LIWC is a transparent text analysis program that counts words in psychologically meaningful categories ...[such as] attentional focus, emotionality, thinking styles, and individual differences” (Tausczik & Pennebaker, 2010, p. 24). LIWC is also a dictionary-based approach comprising more than 100 dictionaries built to capture individuals’ social and psychological conditions in text.³ LIWC scans a given text and compares each word to a list of dictionary terms, calculating the proportion of total words in the text that match each of the dictionary categories.

Even though applying dictionary based approaches is relatively practical, relying on word counts to do interpretations regarding emotions and attitudes in text may require further validation and analysis (van Atteveldt et al., 2021). Recently many researchers have been utilized more advanced methods like BERT on different text classification tasks (Yu et al., 2019).

3.4.3. Pilot Study

To determine the best data analysis approaches and to assess the answerability of the research questions by the proposed methods, I had conducted a pilot study on the data that consists of 452

³ <https://www.liwc.app/help/howitworks>

unique post titles and their corresponding comments, which was a total of 4896 comments. The pilot study was including six subreddits (i.e., r/Futurology, r/Automate, r/DarkFuturology, r/conspiracy, r/artificial, r/tech) from which I formed three main ideology categories about the future of AI (i.e., utopian, dystopian, and neutral) and then examined differences of frames, effects of frames on the attitudes and emotions in these three groups.

In all these processes, I had considered to aggregate two similar subreddits together per each ideology group. Because r/Futurology and r/Automate subreddits generally reflect the positive aspect of the future of AI, I had brought them together into the utopian ideology category. Following this logic, since r/DarkFuturology and r/conspiracy subreddits mainly reflect speculations and negative aspects of the future of AI, I had brought them together into the dystopian ideology category. Lastly, r/artificial and r/tech subreddits reflect general discussions about the future of AI, not polarized ideologies such as utopian and dystopian. I had acknowledged that this categorization might not be conducted by strict boundaries, but I had categorized them as much as possible.

The method I had applied in the pilot study for comparing the three groups (i.e., utopian, dystopian, and neutral) was quasi experiment. There was not a manipulation of the independent variable because I was exploring pre-existing frames embedded in the post titles and comments on these three groups; the selection of groups was not random since ideology groups were formed based on pre-existing subreddits; and it does not include treatment and a control group, rather than that, it includes three groups on which the effects of the independent variable (e.g., frames) to be examined on the grounds of comparing these groups. This method, therefore, was a quasi-experimental (causal-comparative) research method.

Not randomly selecting the participants into groups resulting in a non-equivalent groups design (Zhang, 2022), which was identified as one of the threats to internal validity (Campbell & Stanley, 2011; van Hezewijk, 2009). Since people are self-selecting in to the different subreddits, for the pilot study nonequivalent groups design might have created threats to internal validity in my dissertation work. This potential threat led me to drop ideology groups from the study and not to employ quasi-experimental method in the dissertation work.

In the pilot study, for identifying frames, I had applied LDA topic modelling by using Python Gensim package. I had followed Ylä-Anttila et al.'s (2021) topic modelling approach. They followed three steps for exploring frames using topic modelling and identified the process of completion of these three steps as a frame validation process. First, they determined the number of frames to extract. They found that extracting many topics that result in topics that are too specific, while too few topics result in topics that mix several frames in one. They tested many options including 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100 topics.

At the end of the first step, they found that extracting 30 topics produced topics that are not too specific and not too general or 'mixed'. Second, they looked at the top 10 words for each topic to qualitatively examine the content. They discarded topics that did not constitute internally valid frames that link climate change to a coherent set of other concepts. The second step ended with keeping 17 relevant frames and discarding 13 topics due to the lack of internal coherence. The authors defined this second step as internal validation. In the third stage, the authors read the top 10 documents associated with 17 defined frames to assess whether the documents represented a frame. At the end of this process, the authors achieved 12 final sets of frames. They defined the third step as an external validation process. Thus, their validation and interpretation processes are reflexive processes going back and forth.

Prior to seeing the coherence scores from the LDA modelling, I had set the maximum possible number of frames arbitrarily as 40, a few more than the number in Ylä-Anttila et al. (2021), which was 30. After running an initial analysis, I had determined the optimal number of frames based on the highest coherence score using Gensim's CoherenceModel to calculate topic coherence for topic models with different topic numbers. There is not a specific coherence score threshold for evaluating a model as good or bad, but the purpose behind looking at the coherence score in many of the existing studies in the prior literature was to determine the optimal topic number by choosing the model with the highest coherence score. For example, in Islam's (2019) paper the highest coherence score for the model they selected as their LDA model was 0.3871. In the pilot study, the highest coherence score among the models with the topic numbers from 1 to 30 belong to the models with 14 topics was 0.38, thus the optimal number of frames in that corpus was identified as 14.

Based on 14 frames, LDA yielded the most dominant frame for each post and comment as the frame number, from 0 to 13 (frame 0 to frame 13). For labeling each frame, following Ylä-Anttila et al. (2021), I looked at 10 keywords for a specific frame, 10 posts with the same frame number, and compared these to technological frames stated in Table 2 obtained from the existing literature. If there was a similar frame in the current literature, I gave the frame that name that is associated with this existing relevant frame or embraces this frame.

For this frame identification process, I had removed special characters like @, #, & and did not apply lemmatization or stemming because I intended to protect the naturalness of the data. Redundant manipulation might have caused some losses or deviations from the information to be obtained from the original data. For example, if I had used lemmatization or stemming and had manipulated data, I could not have captured frame terms like anti-aging, machine learning,

imposed, which might have misled me while interpreting the frame terms and finding the frame label names. This might have resulted in loss of meaning or misinterpreting.

This frame analysis revealed the outcomes presented in the preliminary results in the appendices (Appendix A). Although these preliminary results revealed quite informative frames that provide important points embracing versatile insights about the future of AI, I experienced several limitations of LDA topic modelling in the process of conducting the pilot study.

The first limitation of LDA topic modelling method was its neglect of semantic relations among words (Egger & Yu, 2022) since the method focuses on word occurrence probabilities. Second was the necessity of manually determining hyperparameters such as *number of topics* (k) – even though varied methods are applied for this determination like considering the elbow on the graph coherence or perplexity scores, at the first stage k still needs to be defined by users before finding the k that makes the model optimal – and *alpha* (a) – even though topic modelling libraries like Gensim provides α =‘auto’ option, *alpha* that controls the prior Dirichlet distribution over topic weights in each document may be defined by users. Third, LDA does not enable topics to be correlated to each other. Fourth, it generally requires detailed preprocessing (e.g., cleaning, stemming, generating term-document matrices) of the documents since it is based on term-document matrices and sentence structures are not modeled.

These limitations prompted me to find another topic modelling approach that can address these limitations. BERTopic described in the section 3.4.1.1 addresses these limitations and offers more advanced functions such as search functions (e.g., easily going from topic to documents), hierarchical topic modelling and dynamic topic modelling (i.e., illustrating changes in topics over time), thus it is used for the frame detection in this dissertation.

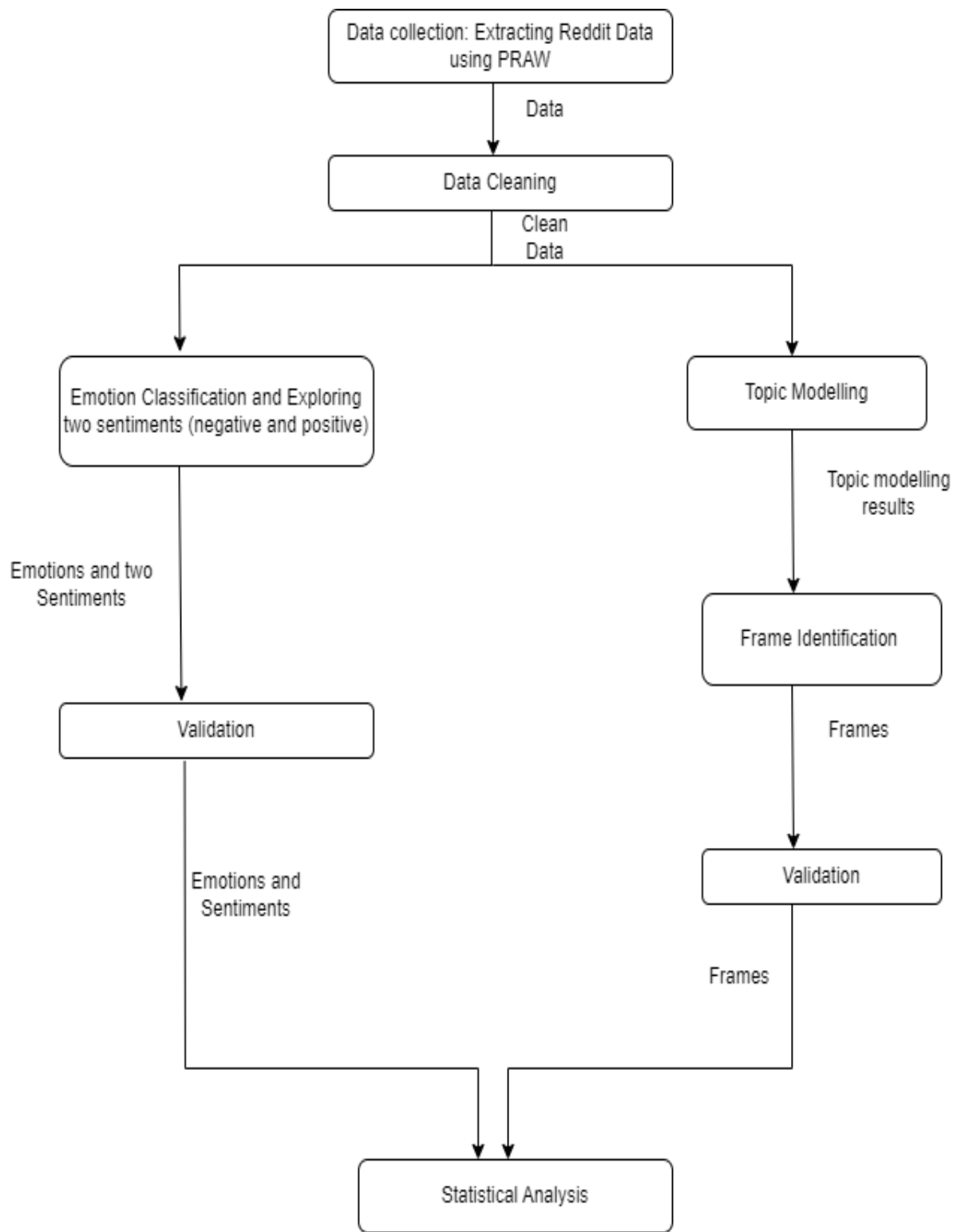
For exploring emotions in the pilot study, I had harnessed NRC emotion lexicon (Mohammad & Turney, 2013) with the R package “syuzhet.” This analysis was a lexical-oriented method in which words extracted from posts and comments are compared with the NRC lexicon’s words list. This word list was built on the grounds of manually annotations by Mechanical Turk crowdsourcing to find associated words with Plutchik’s (1980) eight basic human emotions (i.e., anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two general sentiments (i.e., negative and positive). Syuzhet package was giving emotions and sentiments for each submission, but it did not handle negation words (e.g., I don’t fear). This problem led me to change this sentiment and emotion detection method and to use BERT models.

The main purpose of the pilot study was to examine whether social media users’ thoughts, emotions, attitudes, and motivation can be explored by topic modelling, emotion and sentiment analysis, and statistical tests. The pilot study showed the feasibility, acceptability, and effectiveness of these approaches; however, the specific methods used to apply these approaches can be replaced by more effective and advanced methods such as BERT models, the details of which are described below.

3.4.4. Main Studies

Figure 4 provides an overview of data analysis steps to be implemented that consolidate Studies 1, 2 and 3. The following sections elucidate and justify data analysis processes to be administered for each study from Study 1 through Study 3.

Figure 4. Data Analysis Steps



3.4.4.1. Study 1- AI Frames in Reddit Conversations

The first study seeks to explore AI frames expressed by Reddit users that reflect their relevant future expectations and interpretations.

To discover new patterns related to *AI frames*, I apply topic modelling given its noticeable strong points as stated in the section 3.4.1.1 and its effectiveness for finding frames as shown in the pilot study explained in the section 3.4.3. Despite BERTopic's salient advantages highlighted in the section 3.4.1.1, Egger and Yu (2022) emphasized a few disadvantages that it brings with. First, its embedding approach may result in too many topics, demanding labor-intensive examination of each topic. Likewise, it may produce many outliers.

These mentioned disadvantages, however, are not barriers to the proposed study. There is a function to reduce the number of topics. Moreover, parameters can be customized to reduce the number of topics. To address the limitation concerning outliers, BERTopic specifies outliers by -1, thereby they can be easily excluded from the results. Thus, I use BERTopic model due to its highlighted advantages.

Frame Identification Procedure Implemented in Study 1

Data collection and cleaning procedure was explained in section 3.3. This section describes BERTopic modelling processes. The cleaned text data consisting of post titles and comments were processed in Python for topic modelling. After that, this data is clustered by the BERTopic model. The original model created 231 clusters; 7187 submissions did not belong to any of these clusters shown as -1 that refers to all outliers. To identify and interpret frames properly, I decreased the number of clusters. To do so, first I used topic reducing function as “`model.reduce_topics (documents, topics, nr_topics = “auto“)`” since that function merges clusters together that are very similar, but it still gave me many clusters, 195 clusters, which complicates identifying and interpreting frames and making appropriate inferences. Because of

this, I dove into the algorithms behind BERTopic and set parameters to find a reasonable number of clusters to be interpreted properly.

The algorithms behind BERTopic contains 3 stages: 1) document embedding, 2) document clustering (i.e., by UMAP reducing the dimensionality of embeddings, and by HDBSCAN clustering reduced embeddings and creating clusters of semantically similar documents, 3) creating topic representation (extracting and reducing topics with c-TF-IDF) (Grootendorst, 2022). Because BERTopic model with default parameter values returned many topics, more than 100, and many outliers, I changed the parameters to find the best model and built new BERTopic models by setting new values for parameters for algorithms behind BERTopic. I built 9 customized models and then chose the best model based on *trustworthiness score* which shows how much data remains the same after dimension reduction by UMAP and *density-based clustering validation (DBCV) score* which shows how much the same clusters are dense, and the different clusters are not dense after clustering by HDBSCAN. The best BERTopic model I found through this hyperparameter search yielded 36 clusters. DBCV score for this model was 0.21 and specific hyperparameters were: “min_samples” = 50, “min_cluster_size” = 50, “metric” = “euclidean”, “cluster_selection_method” = “leaf.”

The next step was to find the clusters that were frames. Asmussen and Møller (2019) suggested semantic validation as the best method for confirmation of topic modelling results. Semantic validation means comparing topic modelling results with expert reasoning to see results semantically make sense. Taking this into account, we validated topic modelling results by implementing Heidenreich et al.’s (2019) and Ylä-Anttila et al.’s (2021) semantic validation approach.

More specifically, three interpreters, I as a doctoral student in Information Science and Technology and two master's students one of whom is in Business Analytics and the other is in Applied Data Science named the clusters obtained from topic modelling. Word groups and sample submissions (i.e., Reddit posts or comments) associated with these groups were read until reaching the saturation point for understanding the main idea, examined whether they make sense and then interpreted and categorized by an inductive approach in the light of prior AI framing literature summarized in Table 3. Then we categorized relevant clusters into frames as *risk*, *benefit*, *harm*, and *new world of work*.

To further validate the results, two graduate students annotated a sample of 125 post titles and comments that were classified into *risk*, *benefit*, *harm*, and *new world of work* by BERTopic and then I calculated evaluation scores such as accuracy, precision, etc. The classification done by BERTopic here is based on the most dominant cluster for each post title/comment (See details of frame identification and evaluation scores in Appendices B, C, and D).

3.4.4.2. Study 2- Attitudes and Emotions in Reddit Conversations

Dictionary based emotion and sentiment analysis approaches are relatively practical, but relying on word counts to detect emotions and attitudes in text requires further validation (van Atteveldt et al., 2021). Recent research endeavors applied more advanced methods like BERT on different text classification tasks (Yu et al., 2019) including sentiment and emotion analysis, which I also followed.

For the aim of detecting emotions, I also use a pre-trained multiclass text classification model with BERT and ktrain (Maiya, 2022) and finetuned that through utilizing GoEmotions dataset (Demszky et al., 2020). The specific parameters used for this model include three epochs and a learning rate of $2e^{-5}$. GoEmotions dataset is consisting of 58k English Reddit comments

(Demszky et al., 2020), annotated as 27 emotion categories or Neutral. The categories in this dataset are admiration, amusement, anger, annoyance, approval, caring, confusion, curiosity, desire, disappointment, disapproval, disgust, embarrassment, excitement, fear, gratitude, grief, joy, love, nervousness, optimism, pride, realization, relief, remorse, sadness, surprise.

The emotion detection model I built captures all these 28 categories in text. Using this model, each post title and comment was classified into one of those emotion categories. To validate the results, first a random sample of 125 submissions (Reddit post titles and comments) that the BERT multi class classification model classified into *fear*, *joy*, *anger*, and *sadness* were chosen since the initial proposed hypotheses were focusing on those emotions. Using the code book that includes the determined emotions, their definitions, and examples, sample submissions (see Appendix C), 125 submissions were coded by two graduate students independently.

In addition to these emotion categories stated in the initial hypotheses, we validated classification of new emotion categories to be used in the statistical analysis in Study 3 by annotating new 125 submissions classified into the new emotion categories: curiosity, annoyance, confusion, disapproval, and gratitude. Then, the intercoder reliability score between the students and performance evaluation scores were calculated based on the ground truth created by the students' classification. The accuracy was 0.84 and Cohen's kappa score between the ground truth and machine classification was 0.80, meaning that the emotion classification is valid. The details about the process and evaluation scores are presented in Appendices C and D.

For detecting positive and negative attitudes on the post titles/comments about AI, I built another BERT model that I fine tuned with IMDb Movie Reviews consisting of 50k movie reviews for detecting two valences of sentiment: *positive* and *negative*. The specific parameters used for this model include one epoch and a learning rate of $2e^{-5}$. A validation process similar to

the one for emotion detection was conducted also for attitude classification. A random sample of 150 submissions that were classified into *positive* and *negative* by BERT machine classification were chosen. By using the code book (see Appendix C), 150 submissions were classified by two graduate students independently. After that, the intercoder reliability score between the students was calculated. Following that, based on the ground truth created by these students' classification, performance evaluation scores were measured. The accuracy was 0.91 and Cohen's kappa score between the ground truth and machine classification was 0.83, indicating that the machine coding is valid. The details about the process and evaluation scores are presented in Appendices C and D.

3.4.4.3. Study 3- Examining Social Influence: Testing the Proposed Research Model

The third study tests hypotheses shown in the proposed integrated theoretical research model (see Figure 1) to investigate social influence through analyzing relations of frames embedded in post titles and emotions and attitudes embedded in comments, and the level of engagement (associated with salience). Because commenting behavior is associated with the level of engagement (Choi et al., 2021) and salience is associated with the level of engagement (Entman, 1993), I measured *salience* by looking at the *number of comments*.

The unit of analysis is post title/comment level. I conducted statistical tests using R language: I used chi-square tests to find the relationships among frames, emotions, and attitudes which are categorical data. To explore whether they influence commenting behavior, attracting more users, in other words, whether they make a perceived reality more salient, I examine how these variables influence salience (measured by the number of comments), thus it is count data, Poisson and negative binomial models were conducted; because of overdispersion in Poisson models, the results of negative binomial models were reported in the findings.

Maxwell (2004) claimed statistical tests such as Chi-Square show correlations, but there is not a technique that enables the researchers to verify if a correlation between variables is causal. For addressing this issue, researchers can provide causal explanations corroborating statistical correlations with relevant theories (Maxwell, 2004). On the other hand, researchers such as Xiong (2018) attempted to present several methods for the purpose of discovering causal relationships by combining regression models, structural equation models, and deep learning models (Chén, 2020; Xiong, 2018). There are also some packages for causal inference like R package dagitty⁴ or python package causallib⁵ that integrate different techniques.

However, to better interpret the results and to obtain more detailed information about the variables through proper post hoc tests, we followed Maxwell's (2004) strategy. We intended to observe correlations utilizing statistical tests and to present explanations corroborating the correlations with pertinent theories demonstrated in the research model. Moreover, we benefit from the posts and comments to make these explanations since comments are written as the responses to the posts. For example, when we found a significant relationship between frames in the post titles and sentiments in their corresponding comments using a chi-square test, we interpreted that as "frames influence attitudes," as hypothesized.

⁴ <http://www.dagitty.net/primer/>

⁵ <https://causallib.readthedocs.io/en/latest/>

CHAPTER 4. FINDINGS

4.1. Introduction

This chapter presents the findings of the three studies that form the dissertation. First, the frames found in the first study were presented; second, the emotions and attitudes discerned in the second study were illustrated, and the third section discusses whether the proposed research model that shows the relationships among the variables (i.e., frames, emotions, attitudes, and the level of engagement associated with salience) is validated.

4.2. Study 1 –Technological Frames on Social Media: What do Redditors Think of the Future of AI?

Through the lens of technological frames, the first study aimed to explore AI frames on Reddit conversations, more specifically in the post titles and comments. This study answered this research question:

RQ1: How do social media users frame the future of AI?

Topic modelling results yielded 36 clusters as the result of analyzing the future of AI related conversations. Table B in Appendix B displays these 36 clusters, 10 words that most strongly represent each of them, a descriptive label based on interpretation of these keywords and submissions associated with those clusters, explanations and example submissions associated with these specified labels. The labeling process was described in detail in the data analysis section and in Appendix B. Frame and explanation columns represent “what Redditors think” inferred from this analysis supported by the examples from real post titles and comments presented in the example column.

The most common clusters found in the conversations were the risk of *loss of control*, *benefits of AI* in various domains (cluster19) and *impacts of automation and robots on wealth*

and society, representing 8%, 6% and 5% of the posts and comments, respectively. The least common clusters are *AI and quantum computing* and *singularity*, which were less than 1%.

To identify frames from the clusters, the authors and coders examined each one (e.g., impact on crime) to see if it fits one of the frames of *risk*, *benefit*, *harm* and *loss* from the hypotheses developed in this dissertation. Clusters 3, 15, 23, 25, 29, 34 and 36 were deemed to be associated with risks, cluster 19 with benefits, clusters 4, 8 and 32 with harm and cluster 35 with loss of jobs. The remaining clusters were deemed to represent topics rather than frames and so not used for the study (with two exceptions, described below).

Three of the frames had enough posts for analysis, risks, benefits, and harm. We had chosen a *loss* frame from Plutchik's (2000) theory as in Table 1 as we were expecting to observe many post titles and comments about loss of jobs. However, we found only a few posts with this frame, too small a sample for the planned statistical analysis. Examining the clusters again, we found post titles and comments about employment, unemployment, transformations in work or in jobs, impacts of automation and robots on wealth and society. Therefore, instead of examining *loss*, we created another more comprehensive frame, *new world of work*, consisting of work-related clusters of 2, 10 and 35, which also contain loss of jobs. We discuss below the expected relationship of this new frame to emotions and sentiment.

The sub dataset including only posts and comments and using these four frames contains 5926 rows (as the total of 476 unique post titles and 5450 unique comments), 34% of the entire data (17609 rows as the total of unique post titles and unique comments). The most common frame in this sub dataset was *risk* (48%), the second most prevalent dataset was *new world of work* (21%), the third one was *harm* (18%) and the least common frame was *benefit* (13%). The following sections discuss these frames in more detail.

A) *Risk*

Reddit users express many perceived risks concerning AI. Clusters 3, 15, 23, 25, 29, 34 and 36 were associated with the *risk* frame and show different risks such as the risk of loss of control, the risk of surveillance, the use of AI for malicious purposes, AI usage of personal data for marketing purposes, risks related to racism, discrimination, and bias, spreading disinformation, potential manipulation of people by fake audios, videos, etc. Moreover, *algorithmic warfare*, *fear mongering*, *propaganda machine* metaphors were also observed like *propaganda machine* example in this comment:

The premise behind this technology is one to better humanity but realistically this will eventually be turned into a propaganda machine. I'm not one for conspiracies but I do like to think I'm a realist. So if governments doesn't already have this technology they will soon and there will be a slow integration of what they want people to see vs what is actually happening particularly in countries like the US where the media is heavily influenced by politics...

This example comment exhibits the perceptions about misuse of personal data; surveillance and violating privacy:

Prevent human data from getting into the hands of a powerful few. Way too late.
Cambridge Analytica ring any bells? How about GCHQ; NSA; Edward Snowden.
Probably time to read Harvard Professor Emeritus Shoshana Zuboff's The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power.

The post title of "Calculations Suggest It'll Be Impossible to Control a Super Intelligent AI." is a risk example concerning the belief that humans will lose control of AI. Another post title, "Growth of AI could expand security threats if no action taken. Artificial intelligence tech could

lead to new forms of cybercrime political disruption and physical attacks within five years say experts.” indicates security risks. As a racism and bias related risk example, the post title of “Scientists Built an AI to Give Ethical Advice, But It Turned Out Super Racist.” demonstrates the potential loss of control of AI and risks of racism and discrimination. The example shows AI behaving in a racist manner while it was supposed to provide ethical assistance.

B) New World of Work

The impacts of AI on work were examined by many scholars such as Brynjolfsson & McAfee (2014). The impacts of AI on work can be both positive and negative. By taking over some tasks AI can provide benefits to humans, namely augment humans or by automating all the tasks that were carried by humans before, it may cause workers to lose their jobs. Clusters 2, 10 and 35 were associated with such kinds of interpretations and categorized into the *new world of work* frame.

Cluster 2 exhibits the belief that automation and robots will influence the society and economy, the possibility of social instability (as in the example post “rich people will become richer”), mass unemployment, unequal wealth redistribution, or bringing wealth to everyone stemming from AI, both positive and negative impacts in conversations, and new needs signaled by the people to adapt these impacts, e.g., a need for new arrangements related to tax and universal income. For instance, the post categorized into Cluster 2, “It’s really scary how much widespread unemployment is coming in the very near future. I mean all that anger is going to have to be politically diverted towards some minority group” demonstrates the possibility of unemployment in the coming years. Another example, “we’ve already seen this happen over the two hundred years with the industrial revolution, so it isn’t surprising. We need wealth redistribution in the form of taxes or public ownership of automation,” indicates a need for new

arrangements related to tax and universal income. Cluster 10 focuses on replacing tasks (both automate and augment, more examples are presented in Appendix B, Table B) in different domains as in that example comment:

I think we're going to first see AI attempt to replace low skill or mundane task work but then I wouldn't be surprised if we see some executives try to see if an AI could replace knowledge workers. They'll revel in their means to not have to deal with paying high salaries or worker shortages until one day the AI makes a case that it could also replace the executives and the shareholders agree. My concern is more on if companies start using AI to replace knowledge workers what happens when we have an overload of humans who now can't work and make a living?...

Lastly, Cluster 35 is about loss of jobs, especially in the banking sector as in that example: "This makes me worried. I work at a bank and sometimes think about whether the job I'm doing will even exist years from now. Besides I don't even know whether I can move into another industry now."

C) Harm

Reddit users also express their concerns associated with ***harm*** stemming from AI. Three clusters (Clusters 4, 8 and 32) include conversations about harm.

Cluster 8 is about destruction and ending mankind. More specifically, it is the belief that AI will destroy humanity and mankind will end because of AI as in the example post "sometimes this feels like celebration of human demise." Second, conversations associated with Cluster 4 is about military applications, particularly, the belief that weapons with AI is affecting wars, military, e.g., autonomous weapons, *genie in the bottle*, *algorithmic warfare* metaphors as in the example of "AI robot armies are here to stay. That genie won't go back in the bottle. Just

wait until they get nukes. Nobody will dare to move or even twitch.” Lastly, Cluster 32 reflects perceptions about the harmful behaviors of giant companies and their owners.

D) Benefit

Interpretations related to the AI benefits are also observed in the conversations on Reddit.

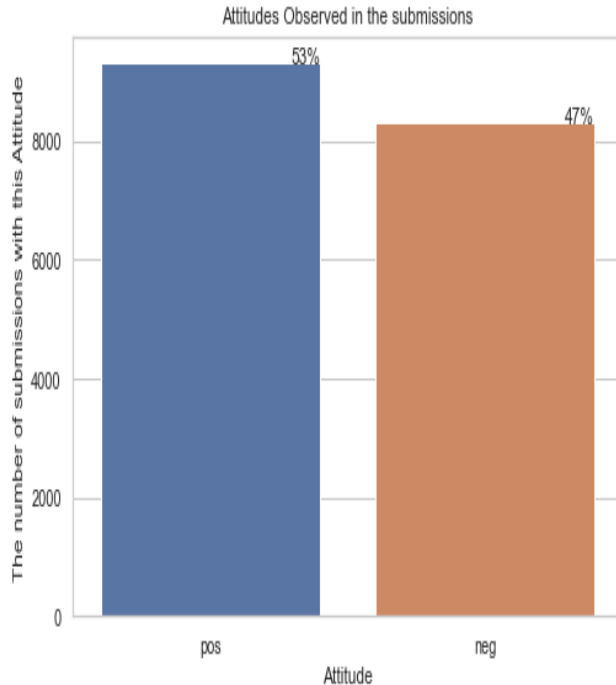
Cluster 19 was associated with benefits since it reflects different AI applications may be useful in different domains. The post title of “Scientific progress may accelerate when artificial intelligence (AI) will explore data autonomously without the blinders imposed by human prejudice,” for instance, indicates the help of AI in the development of scientific progress. In these two post titles, Reddit users point out the benefits of AI in writing and in discovering physical laws in data, respectively: “This Article is Written Completely by GPT. A Top-Notch Artificial Intelligence Algorithm and It Tells Us Not to Worry About the Rise of Artificial Intelligence” and “Japanese researchers developed Artificial intelligence that can discover hidden physical laws in data.”

4.3. Study 2 – Attitudes and Emotions Discerned in Reddit Submissions

As previous research indicates frames influence emotions and attitudes (e.g., Brockner & Higgins, 2001); and emotions and attitudes influence peoples’ level of engagement (Marcus, 2013), this study discerned emotions and attitudes embedded in AI- related Reddit conversations. This study answers this question: *Which emotions and attitudes does the public convey in the future of AI-related conversations on social media?*

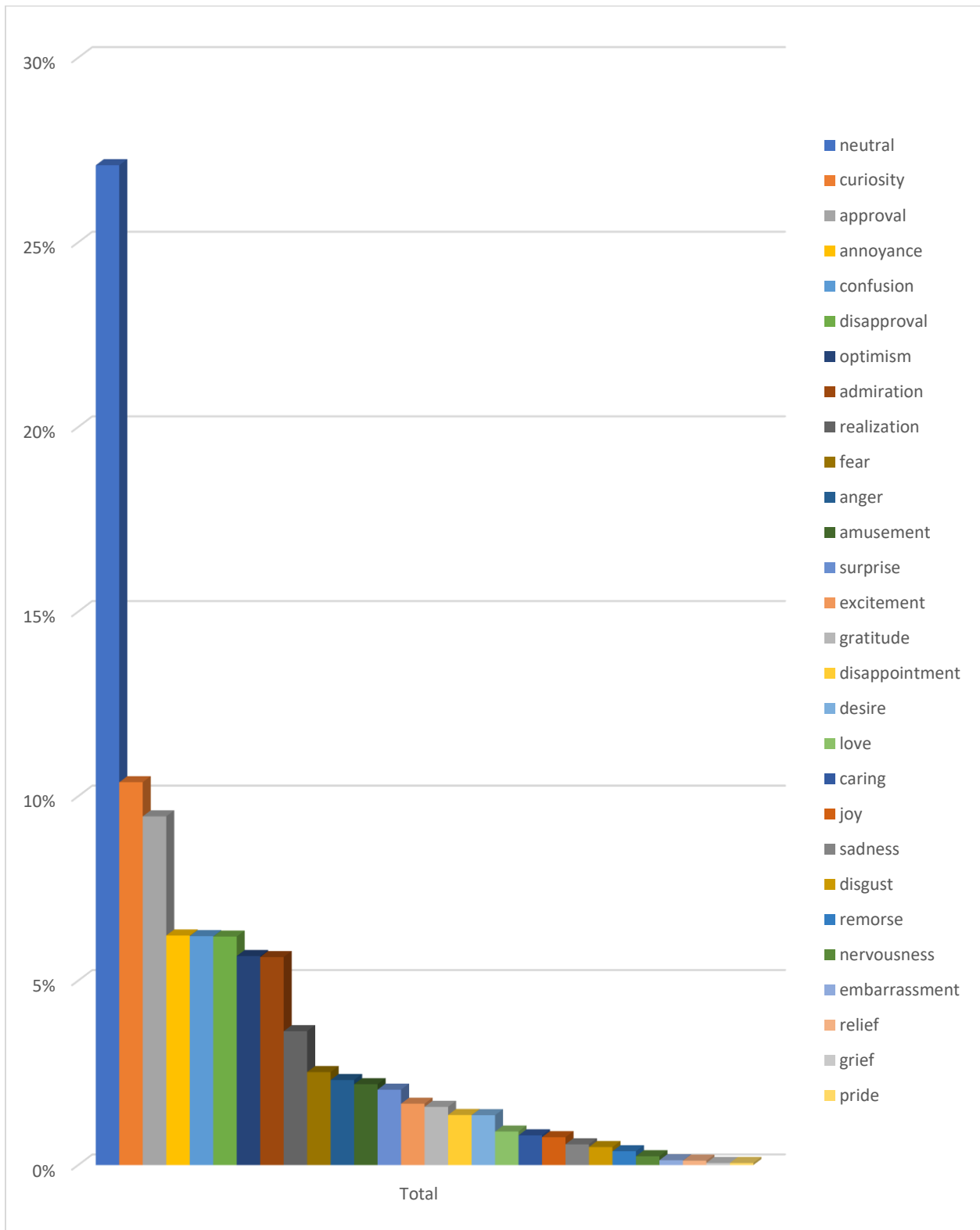
To explore how people feel about the future of AI, first we conducted sentiment analysis to observe the attitudes. The general attitude was slightly positive (53% positive vs 47% negative in the entire dataset). The attitudes observed in the dataset is depicted in Figure 5.

Figure 5. Attitudes Observed in the Entire Data Set



In addition to the attitudes, we aimed to explore common discrete emotions and intended to capture all the emotion categories (admiration, amusement, anger, annoyance, approval, caring, confusion, curiosity, desire, disappointment, disapproval, disgust, embarrassment, excitement, fear, gratitude, grief, joy, love, nervousness, optimism, pride, realization, relief, remorse, sadness, surprise or Neutral) specified in GoEmotions dataset. Most post titles and comments were neutral, the second most common category was curiosity, and the third one was approval. The least common categories were sadness, remorse, grief, pride, relief, and embarrassment. The distribution of emotion categories (excluding neutral) in the corpus is presented in Figure 6. After curiosity and approval, annoyance, confusion, disapproval, and optimism were common in the dataset (see Figure 6).

Figure 6. Emotions Observed in the Entire Data Set



Curiosity was the most common emotion category observed. Various questions regarding the future of AI that demonstrates the curiosity of people were observed on Reddit conversations; for instance, an example question appeared in the discussions about unemployment that involves curiosity:

When the subject of AI comes up there is often a lot of concern about the prospect of AI replacing so many people that it creates widespread unemployment. Can you give us some examples of jobs that might be created by AI?

More general questions such as “how close is AI to being able to take over the world?” also exists. In that example, subsequent questions that comprise ethics, governance arrangements, AI augmented reality and robotics and AI usage in wars.

Should there be a global ethics body on technology including AI? If so, where should that sit and what should the governance arrangements be? What powers should it have? Could that govern for example the development of AI augmented reality and the use of robots in battle?

Approval was also widespread, especially in the posts that indicate applications of AI like article writing as in the example of “This Article is Written Completely by GPT. A Top-Notch Artificial Intelligence Algorithm and It Tells Us Not to Worry About the Rise of Artificial Intelligence.”

On the other hand, negative emotion categories were also present like confusion and disapproval. As seen in the example comment below, some Reddit users encounter confusion:

But what about situations where physics misrepresents reality, I’ve always thought that mathematics and sciences fit the world pretty well but don’t offer any inherent truth or substance. We didn’t discover we invented. Would this not lead to even more biases in AI? I have no idea what I’m talking about.

Disapproval found in the conversations was reflecting different aspects of disapproval. For instance, it could be disapproval of certain AI applications as in the example of “you don’t need AI to say sudden violent and often” or could be not agreeing others’ interpretations as in that comment:

I disagree. Why do we think that something smarter than us wouldn’t appreciate us just for existing? Humans are clearly at least physically different from computers and an infinity smart computer would know that. As humans got smarter and smarter, we went from just living to things like producing art who’s to say that artificial inelegance wouldn’t just create a new renaissance and suddenly we’ll have huge amounts of beautiful artwork. I don’t see why artificial inelegance would be a threat to mankind for anything else than taking our jobs which arguably would be pretty bad but not really danger.

In conclusion, there are varied emotions, both positive and negative emotions, yet positive emotions were slightly more common than those of negative.

The sentiment analysis also showed positivity is slightly more common than the negative attitude. The post titles and comments with positive sentiment were generally about AI advancements that may help humans in different domains, such as biology as in that example “Artificial intelligence system rapidly predicts how two proteins will attach. The machine learning model could help scientists speed the development of new medicines,” or more specifically in health as in the example of “A New Artificial Intelligence Can Help Diagnose Lung Cancer a Year Earlier. It was effective at detecting tumors.”

Post titles and comments with negative sentiment mainly indicate various problems including ethical problems such as in this example:

The next big privacy scare is a face recognition tool you've never heard of. It's a Peter Thiel funded company called Clearview AI and its service matches faces from images you upload with those in its database of some three billion photos pictures have been scraped from millions of websites.

There are other expressions about other problems associated with AI like spreading misinformation as in that example: "Artificial Intelligence World is astonishingly pessimistic says EU research commissioner. Media are too full of alarmist hysterical doomsday scenarios says Carlos Moedas as EU looks at ways to block flow of online misinformation." Some negative post titles and comments point out glitches in AI use, like patent regulation needs as seen in that example: "Artificial intelligence is breaking patent law," and some of them contain negative metaphors and general attitudes towards AI as in "The Metaverse Artificial Intelligence is the AntiChrist."

4.4. Study 3 – Social Influence on Reddit

The third study tested a proposed integrated theoretical research model (see Figure 1) and associated hypotheses stated also in Table 4 established by relevant theories and previous literature explained in Chapter 2.

The hypotheses inspect relationships between dominant frames, emotions, attitudes, and the number of comments to answer this research question: *How do AI frames on social media like Reddit affect social influence (i.e., emotions, attitudes, the level of engagement associated with salience)?*

To test these hypotheses statistical tests were carried out using R. The first set of hypotheses were initially:

H1-1. Comments on posts using a harm frame are more likely to display a negative sentiment than a positive sentiment.

H1-2. Comments on posts using a risk frame are more likely to display a negative sentiment than a positive sentiment.

H1-3. Comments on posts using a benefit frame are more likely to display a positive sentiment than a negative sentiment.

H1-4. Comments on posts using a loss frame are more likely to display a negative sentiment than a positive sentiment.

Since the *loss* frame was replaced by *new world of work*, we consulted again Plutchik's (2000) theory and modified the final hypothesis by considering the new world of work as analogous to "new territory" in Table 1 in the literature review section. New territory is hypothesized to be associated with the emotion of anticipation (Plutchik, 2000), and this emotion with both positive and negative sentiments. As a result, the resulting hypothesis is:

H1-4'. Comments on posts using a new world of work frame are equally likely to display a negative sentiment and a positive sentiment.

To test these hypotheses, a chi-square test was used since frame and attitude are both categorical variables. Because in the light of findings of the first study we changed our focus from *loss* frame and created a more comprehensive frame *new world of work*, the chi-square test included *new world of work* instead of the *loss* frame. The analysis revealed a significant relationship between frames in post titles and attitudes in comments (Pearson's chi-squared test: $X^2(3) = 234.39, p < 2.2e^{-16}$). For the discrete frames, chi square post hoc tests were conducted through

chisq.posthoc.test (M1, method="bonferroni") code which results in adjusted p values to examine specific relationships. The results are shown in Table 6.

Table 6. Chi Square Post Hoc Tests Results for the Relationship between Frames and Sentiments

| Frame | Value | neg | pos |
|-------------------|-----------|--------|--------|
| Benefit | Residuals | -14.46 | 14.46 |
| Benefit | p values | 0.00 | 0.00 |
| Harm | Residuals | 8.17 | -8.17 |
| Harm | p values | 0.00 | 0.00 |
| New world of work | Residuals | - 0.76 | 0.76 |
| New world of work | p values | 1.00 | 1.00 |
| Risk | Residuals | 6. 76 | - 6.76 |
| Risk | p values | 0.00 | 0.00 |

Harm and risk were found to be statistically significantly correlated with negative attitude ($p < .001$), while benefit was correlated to positive attitude ($p < .001$). Thus, H1-1, H1-2, H1-3 are supported. Chi square post hoc tests did not show a significant association between new world of work and a negative or positive attitude, as hypothesized.

The second set of hypotheses was:

H2-1. Comments on posts using a harm frame are more likely to display anger.

H2-2. Comments on posts using a risk frame are more likely to display fear.

H2-3. Comments on posts using a benefit frame are more likely to display joy.

H2-4. Comments on posts using a loss frame are more likely to display sadness.

Because we changed the frame of *loss*, we examined which emotions are related to *new world of work* frame, instead. As noted above, this frame is hypothesized to be related to anticipation, and the closest emotion category to anticipation in our corpus is curiosity. Thus, the revised hypothesis is:

H2-4'. Comments on posts using a new world of work frame are more likely to display curiosity.

For testing the second set of hypotheses, a chi-square test was run since frame and emotion are both categorical variables. This test containing 4 frames and all 28 emotion categories (neutral included) displayed a significant relationship between frames in post titles and emotions in comments (Pearson's chi-squared test: $X^2(81) = 1077.8, p < 2.2e^{-16}$).

Diving into discrete emotions, post hoc tests were conducted as depicted in Table 7. A post title using a *harm* frame has significantly higher probability of being answered with a comment that includes *anger*, *annoyance*, and *disapproval*; thus H1-2 is supported ($p < .01$). Moreover, a significant negative relationship was found between *harm* and *curiosity* and *gratitude*. There was a significant relationship between a post title using a *risk* frame and *fear* in the corresponding comments as hypothesized, thus H2-1 is supported. Moreover, the frame of risk was found to be negatively correlated with *curiosity* and *gratitude*. The third hypothesis that suggests a post title using the *benefit* frame is answered with a comment that includes *joy* emotion was not supported, i.e., H2-3 is not supported. Instead of *joy*, *anger*, *annoyance*, *fear*, *optimism*, and *disapproval* had significant negative relationships with the frame of *benefit*, while *confusion*, *curiosity*, and *gratitude* had significant positive relationships with *benefits*. Finally, post titles containing *new world of work* were not related to anticipation as expected, hence H2-4' is not supported. Instead, a significant negative relationship was found between post titles containing *new world of work* frame and *curiosity* and *gratitude*, and a significant positive relationship with *optimism*. In conclusion, even though frames influence emotions, they influenced different emotion categories, I presented these significantly related emotions in Table 7.

Table 7. Chi Square Post Hoc Tests Results for the Relationship between Frames and Emotions

| Frame | Value | Emotion Category | | | | | | | |
|----------------------|-----------|------------------|-------|-----------|-----------|-----------|-------------|-----------|----------|
| | | anger | fear | annoyance | confusion | curiosity | disapproval | gratitude | optimism |
| Benefit | Residuals | -5.33 | -5.47 | -5.29 | 6.2 | 22.94 | -4.87 | 12.65 | -5.16 |
| Benefit | p values | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Harm | Residuals | 9.25 | 1.93 | 3.86 | -1.98 | -8.37 | 4.16 | -5.36 | -0.47 |
| Harm | p values | 0.00 | 1.00 | 0.01 | 1.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| New world of work | Residuals | -2.54 | -0.64 | -0.34 | -3.13 | -7.75 | 3.18 | -3.94 | 7.04 |
| New world of work | p values | 1.00 | 1.00 | 1.00 | 0.20 | 0.00 | 0.16 | 0.01 | 0.00 |
| Risk | Residuals | -1.21 | 3.91 | 1.72 | -1.6 | -7.95 | -1.72 | -3.8 | -0.18 |
| Risk | p values | 1.00 | 0.01 | 1.00 | 1.00 | 0.00 | 1.00 | 0.02 | 1.00 |

The third set of hypotheses was:

H3-1. The emotion category of anger in posts will be positively related to salience of the technology-related post titles, compared to neutral.

H3-2. The emotion category of fear in posts will be positively related to salience of the technology-related post titles, compared to neutral.

H3-3. The emotion category of joy in posts will be negatively related to salience of the technology-related post titles, compared to neutral.

H3-4. The emotion category of sadness in posts will be positively related to salience of the technology-related post titles, compared to neutral.

Because we examined which emotions are related to *new world of work* frame, instead of *loss* frame, and Lazarus linked anticipation (*curiosity* is used since it is the closest emotion in the corpus) to more engagement, we revised the hypothesis as:

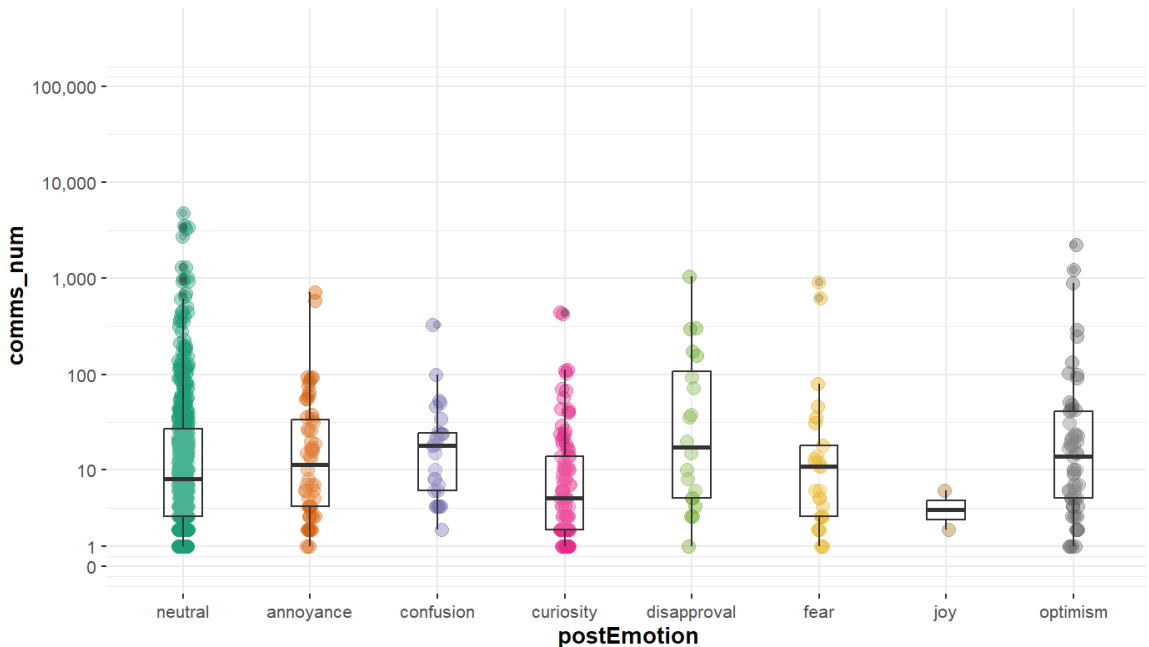
H3-4'. The emotion category of *curiosity* in posts will be positively related to salience of the technology-related post titles, compared to neutral.

The dependent variable, salience of the technology-related post titles is associated with *the level of engagement* and measured by *the number of comments*. We included the post titles classified into the *anger*, *fear*, *joy*, and *curiosity* categories to test the hypothesis. In addition to them, the emotions that were found to be statistically-significantly correlated with the four determined frames (i.e., *annoyance*, *confusion*, *disapproval*, *optimism*, and *gratitude*) and neutral were also added, the number of post titles in this dataset is 774.

Before examining whether there is a significant relationship between salience of the post titles and emotions existed in the posts, how the number of comments is distributed among the

emotion categories chosen is showed in Figure 7 (the number of comments was converted to logs to better interpret the results).

Figure 7. Distribution of the Number of Comments among Emotion Categories in the Posts



To assess the third set of hypotheses, as the dependent variable, salience, is measured by the number of comments, thereby it is count data. First a Poisson model was tested. The Poisson model requires that the mean and variance of the dependent variable are equal. If the conditional variance is greater than the mean, it shows overdispersion of the data, which may result in biased statistical tests. In such cases, the negative binomial model is recommended, as it allows for overdispersion without biased estimates. When the Poisson model was applied, a big difference between variance and mean was found, and dispersion test revealed that over-dispersion was present, so a negative binomial model is appropriate to assess these hypotheses.

A negative binomial model was conducted to assess the relation of the emotions in posts to the number of comments. The results are shown in Table 8.

Table 8. Negative Binomial Regression for the Relationship between Emotions in Posts and Salience

| | Estimate | Std. Error | z value | Pr(> z) |
|------------------------|----------|------------|---------|--------------|
| (Intercept) | 4.40805 | 0.07504 | 58.74 | < 2e-16 *** |
| postEmotionannoyance | -0.59074 | 0.23964 | -2.47 | 0.01370 * |
| postEmotionconfusion | -0.95240 | 0.32537 | -2.93 | 0.00342 ** |
| postEmotioncuriosity | -1.28714 | 0.18959 | -6.79 | 1.13e-11 *** |
| postEmotiondisapproval | 0.33731 | 0.38054 | 0.89 | 0.37541 |
| postEmotionfear | -0.10344 | 0.34230 | -0.30 | 0.76251 |
| postEmotionjoy | -3.02169 | 1.23215 | -2.45 | 0.01419 * |
| postEmotionoptimism | 0.24724 | 0.23341 | 1.06 | 0.28949 |

Observations 774
R squared 0.257

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The emotion categories of joy, curiosity, confusion, and annoyance are significant predictors of the number of comments. Converting to the coefficients, we found: For joy, $e^{-3.02} = 0.05$, for curiosity $e^{-1.29} = 0.28$, for confusion $e^{-0.95} = 0.39$, and for annoyance $e^{-0.59} = 0.55$. These results mean one unit increase of joy in posts is associated with an approximately 95 % decrease in the number of comments, curiosity is so with 72 %, confusion is so with 61 % and annoyance is so with 45 %. Thus, the emotions in the posts in general are related to salience, thereby H3 in general was supported, all the significant emotions found are decreasing the number of comments. Optimism and disapproval are increasing the number of comments, but they are not significant based on this test. R^2 for this model is 0.26, which means 26 % of variance on the dependent variable can be explained by the independent variables, thus indicating that independent variables have 26 % influence on the dependent variable, which is weak, but close to a moderate effect.

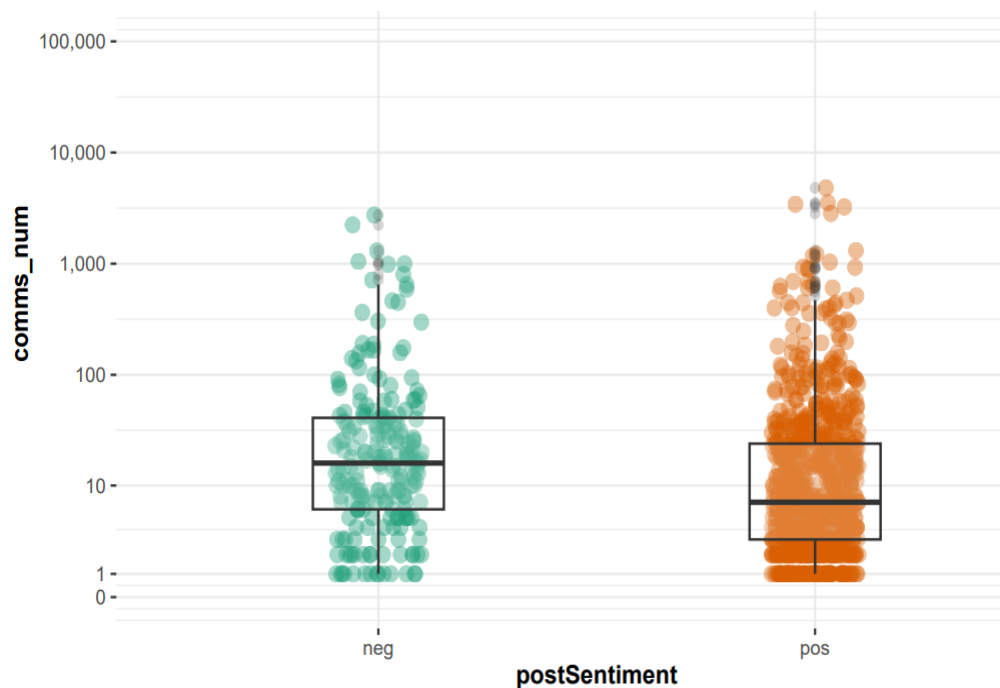
The fourth set of hypotheses was:

H4-1. Positive sentiment in posts will be negatively related to salience of the technology-related posts.

H4-2. Negative sentiment in posts will be positively related to salience of the technology-related posts.

Before investigating whether there is a significant relationship between salience of the post titles and sentiments existed in the posts, how the number of comments is distributed among the sentiments is showed in Figure 8 (the number of comments was converted to logs to better interpret the results).

Figure 8. *Distribution of the Number of Comments among Sentiments in the Posts*



To investigate whether there is a significant relationship, first a Poisson model was tested but due to overdispersion, a negative binomial model was chosen. The results are shown in Table 9.

Table 9. Negative Binomial Regression for the Relationship between Sentiments in Posts and Salience

| | Estimate | Std. Error | z value | Pr(> z) |
|------------------|----------|------------|---------|-------------|
| (Intercept) | 4.5122 | 0.1155 | 39.05 | < 2e-16 *** |
| postSentimentpos | -0.3580 | 0.1294 | -2.77 | 0.00566** |

Observations 1042
R squared 0.029

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The results showed sentiment is a significant predictor of the number of comments, $B = -0.36$, $p = .00566$. More specifically, $e^{-0.36} = 0.70$, which means each unit increase positive sentiment in posts is associated with approximately 30 % decrease in comments. Thus, the fourth set of hypotheses was supported. R^2 for this model is 0.029, which is a weak effect.

The fifth set of hypotheses were initially:

H5-1. Posts using a harm frame increases salience of posts.

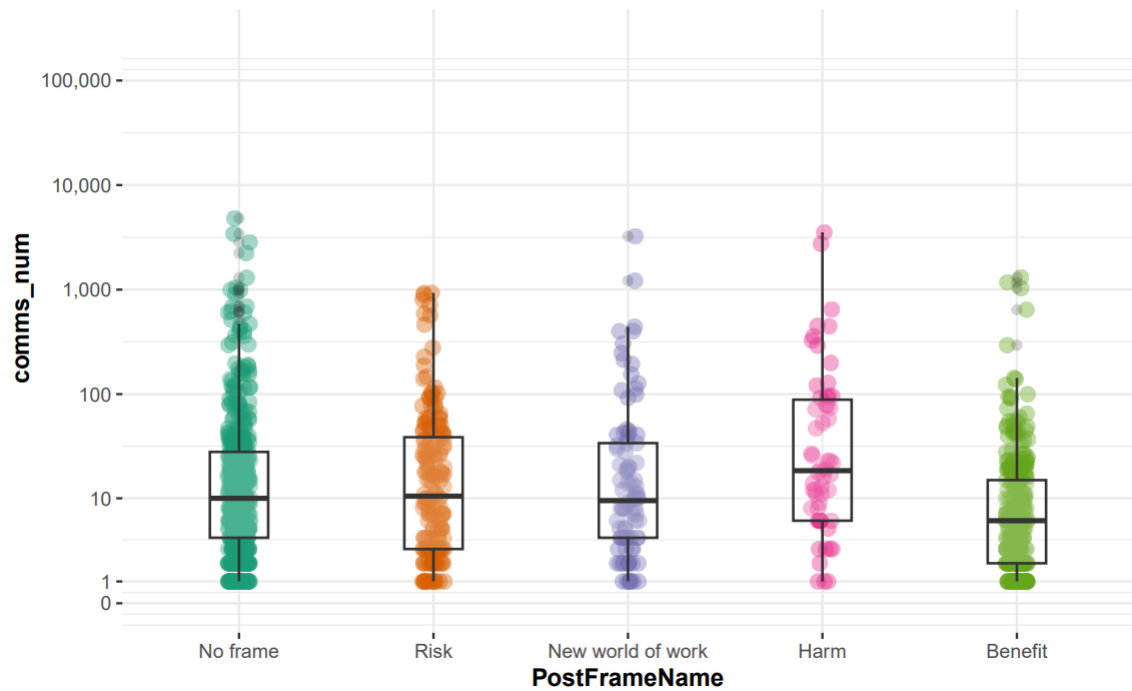
H5-2. Posts using a risk frame increases salience of posts.

H5-3. Posts using a benefit frame decreases salience of posts.

H5-4. Posts using a new world of work frame increases salience of posts.

Before exploring whether there is a significant relationship between salience of the post titles and frames existed in the posts, how the number of comments is distributed among the emotion categories chosen is showed in Figure 9 (the number of comments was converted to logs to better interpret the results).

Figure 9. Distribution of the Number of Comments among Frames in the Posts



For the fifth set of hypotheses, another Poisson model was tested. However, due to the overdispersion, a negative binomial test was instead utilized to find the frames in posts that are significant predictors of the salience of posts. The results are shown in Table 10.

Table 10. Negative Binomial Regression for the Relationship between Frames in Posts and Salience

| | Estimate | Std. Error | z value | Pr(> z) |
|----------------------|----------|------------|---------|--------------|
| (Intercept) | 4.33903 | 0.07614 | 56.99 | < 2e-16 *** |
| PostFrameNameRisk | -0.23766 | 0.14764 | -1.61 | 0.107448 |
| PostFrameNameNWW | 0.17852 | 0.18868 | 0.95 | 0.344058 |
| PostFrameNameHarm | 0.85546 | 0.22793 | 3.75 | 0.000175 *** |
| PostFrameNameBenefit | -0.94623 | 0.12682 | -7.46 | 8.56e-14 *** |

Observations 1042
R squared 0.250

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Harm framed posts had more comments ($B = 0.86, p = 0.0002$) and *benefit* framed posts had less comments ($B = -0.95, p = 8.56e^{-14}$), and $e^{0.86} = 2.35$ and $e^{-0.95} = 0.38$. One unit increase in harm frame is expected to increase the number of comments by 135 % and one unit increase in benefit framed posts is expected to decrease the number of comments by 62 %. Thus, H5-1 and H5-3 were supported. R^2 for this model is 0.25, which is a weak, but close to moderate effect.

Lastly, to explore whether frames in the post titles are significantly related to frames in their corresponding comments, a chi square test was carried out. Frames in post titles and their corresponding comments were found significantly associated (Pearson’s chi-squared test: $X^2(9) = 4035.9, p\text{-value} < 2.2e^{-16}$). More specifically, *benefit* is positively related to *benefit*, *risk* is so with *risk*, *harm* is so with *harm* and *new world of work* is so with *new world of work* based on the chi square post hoc tests as depicted in Table 11.

Table 11. Chi Square Post Hoc Tests Results for the Relationships Between Frames in the Post Titles and Frames in the Comments

| Frame in the Comments | Value | Frame in the Posts | | | |
|-------------------------|-----------|--------------------|--------|--------|--------|
| | | Benefit | Harm | NWW | Risk |
| Benefit | Residuals | 24.76 | -12.7 | -8.74 | 1.72 |
| Benefit | p values | 0.00 | 0.00 | 0.00 | 0.00 |
| Harm | Residuals | -8.33 | 37.21 | -15.00 | -11.55 |
| Harm | p values | 0.00 | 0.00 | 0.00 | 0.00 |
| New world of work (NWW) | Residuals | -9.97 | -11.08 | 47.28 | -23.99 |
| New world of work (NWW) | p values | 0.00 | 0.00 | 0.00 | 0.00 |
| Risk | Residuals | -6.44 | -11.97 | -19.05 | 28.98 |
| Risk | p values | 0.00 | 0.00 | 0.00 | 0.00 |

4.5. Summary of Findings

In summary, in addition to validating the proposed model that shows the relationships among the elements depicted in the model (Figure 1), I looked at the discrete emotions and sentiments and their associations with AI frames. I adapted Plutchik’s (1980, 2000) theory presented in Table 1

to technology setting and added the sentiment and salience columns as parallel to the proposed research model and expected associations among them based on the literature synthesis described in the literature review section. The selected frames and emotions that may be applicable to technology setting, emotions, sentiments, and their possible connections derived from the literature synthesis were presented in Table 4 as social influence sequence in technology-related conversations. Based on that table we developed the hypotheses.

In the hypotheses, first we had risk, harm, benefit, and loss frames as seen in Table 4. Due to the very limited number of loss related frames and post titles and comments, we did not include loss frame in the analysis. Likewise, the number of post titles and comments associated with the category of sadness was also very low. During the frame identification process, we encountered a new more comprehensive frame embracing employment, unemployment, automation and loss of jobs and labeled that as new world of work and found a relevant frame in the Plutchik’s (1980, 2000) theory presented in Table 1.

We devised “new territory” as its analog cognitive element and we considered its corresponding emotion as curiosity as analogous to anticipation (Plutchik, 1980). Furthermore, Plutchik (1980) had linked anticipation to more engagement, thus we hypothesized anticipation is positively related to salience. Then, we modified the hypotheses and investigated whether the relationships exist shown in Table 12 below.

Table 12. Social Influence Sequence in Technology-related Conversations (Modified Hypotheses)

| Technological Frame in Post titles (Stimulus) | Technological Frame in Comments (inferred cognition) | Emotions in Comments | Sentiments in Comments | Salience of the Posts |
|---|--|----------------------|------------------------|-----------------------|
|---|--|----------------------|------------------------|-----------------------|

| | | | | |
|---------------------|---------------------|-----------|----------------------|------|
| “Risk” | “Risk” | Fear | Negative | More |
| “Harm” | “Harm” | Anger | Negative | More |
| “Benefit” | “Benefit” | Joy | Positive | Less |
| “New world of work” | “New world of work” | Curiosity | Positive or Negative | More |

As parallel to the information in the first two columns of Table 12, frames in the post titles are significantly related to frames in their corresponding comments: benefit is positively associated with benefit, risk is so with risk, harm is so with harm and new world of work is so with new world of work (see Table 11). As the hypothesis suggests, the harm frame in the post title was found to be significantly related to the emotion of anger. In addition to that, harm was found positively related to annoyance and disapproval, and negatively related to curiosity and gratitude. A significant positive relationship between risk frame and fear was found, as hypothesized, and risk was also significantly negatively related to curiosity and gratitude. Benefit was found to be positively related to confusion, curiosity, gratitude while negatively related to anger, fear, annoyance, disapproval, and optimism. As for the frame of new world of work a significant negative relationship was found between that frame and curiosity and gratitude and a significant positive relationship was found with optimism (see Table 7).

I also look at the relationships between the emotions in the comments and the sentiments in the comments. Harm and risk frames were significantly related to the negative sentiment, while the frame of benefits was significantly related to the positive sentiment. On the other hand, there was not a significant relationship between the frame of new world of work and positive or negative sentiment. I found negativity is related to the higher level of salience. I also found that the post titles with harm frame are responded by a greater number of comments and those with

benefit frame are responded by a fewer number of comments, thus it is less salient. Table 13 summarizes all the findings.

Table 13. Social Influence Sequence in Technology-related Conversations (Based on Findings)

| Technological Frame in Post titles (Stimulus) | Technological Frame in Comments (inferred cognition) | Feelings in Comments | Attitudes in Comments | Salience of the Posts based on Posts' Frames |
|---|--|--|-----------------------|--|
| “Risk” | “Risk” | fear, - curiosity, - gratitude | Negative | Not significant |
| “Harm” | “Harm” | anger, annoyance, disapproval, - curiosity, - gratitude | Negative | More |
| “Benefit” | “Benefit” | - annoyance, - anger, - fear, - disapproval, - optimism, confusion, curiosity, gratitude | Positive | Less |
| “New world of work” | “New world of work” | optimism - gratitude - curiosity | Negative/Positive | Not significant |

CHAPTER 5. CONCLUSION

This chapter includes the discussion of the findings with implications, limitations and suggestions for future research and the dissertation conclusion.

5.1. Discussion

Today 70% of smartphone owners use a voice assistant on their device (Voicify, 2019). We witness many AI applications like chatbots interacting with customers in commercial company websites, social media bots (e.g., Facebook, Twitter, Reddit bots), social bots chatting to human users (e.g., Eliza representing a mock Rogerian psychotherapist) (Dalgali & Crowston, 2020b), algorithmic journalism generating and editing content, combining databases with editor-created story templates to generate stories (Dalgali & Crowston, 2020a), and various AI applications addressing diverse tasks including image recognition, machine translation (Dalgali & Crowston, 2019), guidance for automated vehicles, and natural language processing tasks. The development of AI applications in various domains is still growing and creating changes in our daily lives. Thus, understanding how people think about the future of AI is important for deployment, development of the applications and for organizing relevant policies that respond to users' expectations and concerns.

To explore such expectations and concerns, surveys were conducted. For instance, Frey and Osborne (2017), Grace et al. (2018) and Walsh (2018) aimed to explore interpretations of domain experts about the future of AI (Walsh compared these interpretations also with nonexperts' interpretations). Walsh suggests that even if some tasks may be automated in certain occupations, experts do not expect full automation with AI usage for the next two decades. The experts in Grace et al.'s study predictions were examining the certain tasks, more specifically, at

which task machines would be better than humans in the near future, e.g., for example, their findings estimated that AI can better translate languages by 2024, write a bestselling book by 2049, and work as a surgeon by 2053. Interestingly, the respondents in Grace et al.'s survey viewed reaching human level machine intelligence as a positive advancement. Prior literature on framing AI such as Fast and Horvitz (2017) also emphasized generality of positivity towards the future of AI.

The findings of this dissertation yielded similar results in terms of positivity and displayed the general picture of what people think and feel about the future of AI. However, people also share their expectations such as regulation needs related to eliminate potential risks such as surveillance, malicious use of AI, privacy violation, discrimination, bias, social inequality, and breaking patent laws. In the second study we found the most two widespread emotion categories as curiosity and approval, and sentiment analysis results also showed positivity slightly outweighs negativity.

In the first study, we encountered versatile interpretations in the future of AI related conversations, from *loss of jobs* to *risk of spreading disinformation*. We categorized the relevant ones into overarching frames as *risk*, *benefit*, *harm*, and *new world of work* as appropriate to the previous relevant literature. We were expecting to have many Reddit submissions with *loss* frame since loss of jobs due to AI have been discussed for a long time, thus we had first *loss* frame instead of *new world of work*. But instead of loss frame, we observed varied interpretations about the impacts of AI on work in different aspects, both positive and negative. Comments and post titles classified as replacing tasks, for instance, were reflecting creation of new jobs, integrating robots enhanced with AI into the workplaces, also loss of jobs, and other

possible transformations in workplaces. Thus, we modified the *loss* frame as the *new world of work* frame.

The second study revealed positivity is slightly dominant and curiosity is the most common emotion category. Even though positivity in general is hardly dominant in conversations, the dominant frame expressed in conversations is *risk* and different types of risks are stated as demonstrated in Findings Chapter. In the third study, combining the findings of the first and second studies we tested the theoretical research model we proposed. For instance, certain frames like benefit are positively related to others' curiosity, which increases their positive attitude but decreases the level of engagement. This model exhibited potential social influence drivers in technology context.

Social influence is our “thoughts, feelings, and behaviors [that] respond to our social world” (Heinzen & Goodfriend, 2019, p. 3). Some studies in the existing literature about framing theorized frames as a public interpretative tool that influence everyone and always evoke responses (Wood et al., 2018). These responses can be thoughts, feelings, and behaviors, thereby building social influence, and social media is one of the most important platforms where social influence is encountered. Framing was found one of the social influence drivers in the prior literature as in Venkatesan and Valecha (2021) measuring social influence by the level of engagement, and more specifically by the number of retweets. In addition to the level of engagement, the effects of framing on emotions, attitudes and behaviors have also been indicated by previous studies such as Lee and Choi (2018) and Marcus et al.(2019).

What emotional and attitudinal responses are related to AI frames, which may constitute social influence, however, have not been explored to date. Specific technological frames like AI frames may be used in the future as proper to specific technologies that could be used to spread

the properties of that technology. The third study, therefore, investigated whether AI frames create social influence on social media. To explore that, we looked at possible relationships between AI frames in post titles and emotional and attitudinal responses, and the level of engagement with the conversations in the light of hypotheses we developed based on the general framing literature.

The results showed that the risk frame in posts were responded with the comments that include fear, and the harm frame with the emotion of anger, as in Plutchik's theory. However, the benefit frame was responded with *curiosity, confusion, and gratitude* in contrast to the hypothesis that suggests *joy*. The reason behind that could be that the future of AI related conversations about benefits of AI applications evoke *gratitude* but also *curiosity* and *confusion* since there is also ambiguity and skepticism in actors' minds instead of a direct feeling of *joy*. Additionally, *optimism* in comments was negatively related to the corresponding posts with *benefit* frame, which may be again due to ambiguity.

New world of work framed post titles were responded with *optimism*, on the other hand, which is an interesting finding. First, we were expecting to see many conversations about the loss of jobs stemming from automation and negative emotions like *fear, sadness*; however, the results showed that Redditors are responding with *optimism* when they encounter new world of work frame in the future of AI related conversations.

The harm and risk frames in posts were responded with the comments with negative sentiment, while the benefit frame was responded with positive sentiment. In contrast, there was not a significant relationship between the frame of new world of work and positive or negative sentiment, as hypothesized. Lastly, we found negativity increases the level of engagement, as parallel to that, harm frame increases the level of engagement while benefit frame decreases it. In

Plutchik's emotion sequence, emotions were connected to behaviors and effects. In this study, we focused on attitudes and commenting behavior by connecting it to the level of engagement and salience.

The implications devised from these findings are presented in the following sections.

5.2. Implications, Limitations, and Future Directions

5.2.1. Practical Implications and Relevant Suggestions for Future Research

The findings of the first and the second studies in this dissertation can enrich current public voice-centric explorations of perceived future of AI, expectations, and interpretations through the lens of technological frames and feelings about the future of AI since they present relevant general interpretations, emotions and attitudes.

In addition to these explorations, the third study examined how technological frames, more specifically, how AI frames are related to emotions, attitudes and commenting behavior of the others encountered these frames, measured by the number of comments, thus associating it with the level of engagement. Table 2 in the literature review chapter quoted from the paper by Spieth et al. (2021) that reviewed the research on technological frames from 1994 to 2020 illustrates the constructs related to these frames including their antecedents and consequences. The consequences shaped by technological frames illustrated in that table were collective sense-making of that technology, directing peoples' attention to the specific features of that technology, the development, and usage of the technology.

Anthony (2018), for example, studying how threats and opportunity frames influence acceptance or questioning of the technology. Spieth et al. (2021) also emphasized technological frames affect the actors' attitudes towards that technology and their reactions. In the third study, as different from the previous methods, rather than directly looking at how these frames

influence the actors' technology acceptance and use, we looked at how the social media users react to these frames encountered in technology related conversations, which also comprises responses such as disapproval, confusion, curiosity, positive and negative attitude. Harm framed posts, for example, were positively correlated with their corresponding comments that include disapproval and negative attitude, and negatively related to curiosity. In contrast, benefit framed posts were negatively correlated with disapproval, and positively related to curiosity and positive attitude.

These emotions and attitudes that are related to frames may also shape behaviors such as technology use or at least their intention to use that technology, which this study did not explore. In addition to those, there may be other variables (e.g., supporting usage of that technology, etc.) influenced by AI frames. These other variables may be examined by further studies. Last but not least, prior work points out that frames are influenced by personal experiences or other personal traits, which this research did not explore. Additionally, individuals' prior beliefs are also related to both cognitive bias and decision making (Acuna, 2011), so prior beliefs may also influence the choice of technological frames. Future research may investigate how personal experiences, personal characteristics and their relevant prior beliefs affect individuals' technology frames in text. Additionally, responses to frames may also vary depending on the individuals' personal experiences, personal characteristics, and their relevant prior beliefs. Such possible differences can also be examined.

Besides technology users, technological frames may also manipulate managers' decision-making behavior related to technology use or support of its use. For example, Benschop et al.'s (2022) research revealed that newly proposed information systems are framed more positively, while the existing information systems are framed with more negative adjectives. This

type of framing could cause a subconscious bias on decision-makers regarding investing in new information systems projects (Benschop et al., 2022). Similar but more comprehensive studies may be carried out covering both AI and IS projects and follow-up investigations as to managers' various decision-making processes regarding these technologies, not just exploring how different systems are framed. For example, do the managers more invest in the systems that are framed with more positive words?

Similar research may be implemented in diverse information systems (IS) research because the IS field may take a critical role in the use of AI (Ågerfalk et al., 2022). Future studies could investigate the similarities and differences between the phenomenon of AI and IS through the lens of framing, for example, how different organizations frame various IS and AI systems in their organizations: do these framing differences or similarities influence decision-making processes in the organizations, like inventing certain technologies more? Do these framing processes help overcome barriers to the adoption of AI in organizations or cause new barriers or hesitations to use these technologies?

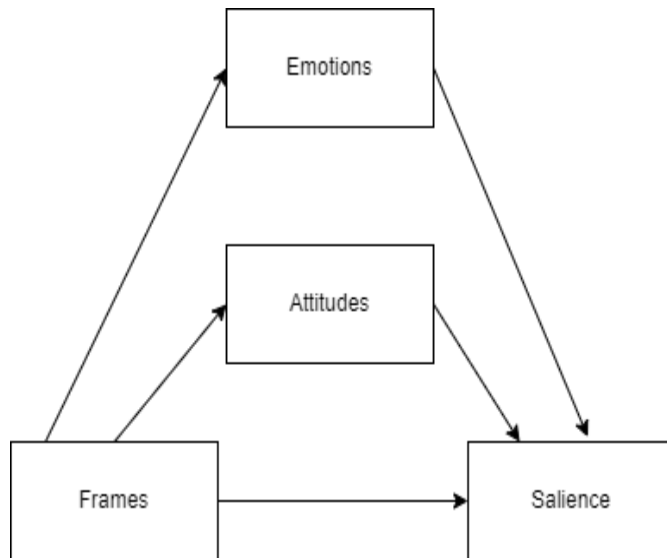
In the third study, we found how AI frames are related to emotions, attitudes, and commenting behavior that may constitute social influence. We found negative frames like harm and negative attitudes significantly attract more users, increasing the level of engagement. Thus, negative frames and attitudes might provoke social media users, thus it may build social influence. The exploration of drivers of social influence on social media in the context of technology might be used in both ways: benevolent or malicious way, to increase the public awareness about the properties of the technology or to provoke the actors. Measures (e.g., restrictions, regulations, etc.) might be taken to facilitate their usage in a benevolent way and to hinder that of malicious way.

5.2.2. Theoretical Implications and Relevant Suggestions for Future Research

Aside from the empirical findings, another crucial implication of this work is application of theory of technological frames (Orlikowski & Gash, 1994) for systematizing the interpretations of the similarities and variations in how people conceptualize the future of AI. Davidson (2006) advocates that manipulation or encouragement for technology use is associated with technology frames, thus understanding frames is critical. Orlikowski and Gash (1994) suggest that technological frames provide “an interesting and useful analytic perspective for explaining and anticipating actions and meanings that are not easily obtained with other theoretical lenses” (Orlikowski & Gash, 1994, p. 174). This work intended to apply this useful perspective for explaining the public interpretations.

Moreover, we had proposed an integrated model (illustrated in Figure 1 and 10).

Figure 10. Final Research Model



As Lazarus (1991) pointed out in their theories, *cognition*, *emotion* and *behaviors* (commenting in this study, associated with the level of engagement and saliency) are harmonically integrated constructs. Inspired by this integration and synthesizing the prior literature, we presented and

validated that model from which we inferred *technological frames* shape *emotions, attitudes, and salience* as in Figure 10.

Synthesizing the prior literature, we presented discrete frames, emotions, and sentiments, and their relationships depicted in Table 12. Those relationships were tested, and Table 13 was created based on the findings (see details in Findings Chapter), thereby we propose social influence sequence in technology-related conversations.

Table 12. Social Influence Sequence in Technology-related Conversations (Modified Hypotheses)

| Technological Frame in Post titles (Stimulus) | Technological Frame in Comments (inferred cognition) | Emotions in Comments | Sentiments in Comments | Salience of the Posts |
|---|--|----------------------|------------------------|-----------------------|
| “Risk” | “Risk” | Fear | Negative | More |
| “Harm” | “Harm” | Anger | Negative | More |
| “Benefit” | “Benefit” | Joy | Positive | Less |
| “New world of work” | “New world of work” | Curiosity | Positive or Negative | More |

Table 12 was created based on Plutchik's emotion sequence (see Table 1). In Plutchik's (2000, p. 69) emotion sequence, each frame is associated with only one of the eight primary emotions (i.e., anger, fear, joy, sadness, anticipation, surprise, acceptance, disgust). For example, risk (its original version was threat) is related to only fear, harm with anger, and so on. In the earlier version of this emotion sequence (Plutchik, 1980, p. 16), some frames were associated with more than one emotion category, but they are additional emotions accompanying the main eight emotions. For example, fear and terror together were the response to a risk frame, and anger and rage, to a harm frame, but the primary eight emotions were separate.

In this study, however, we found that frames were related to more than one of the emotions specified as Plutchik's eight primary emotions. For example, we found that a benefit frame was positively related to *confusion*, *curiosity*, *gratitude* while negatively related to *anger*, *fear*, *annoyance*, *disapproval*, and *optimism*. A risk frame was negatively related to *curiosity* and *gratitude* in addition to a significant positive relationship with *fear*. Harm was positively related to *annoyance* and *disapproval* in addition to *anger*, and negatively related to *curiosity* and *gratitude*.

As for the frame of new world of work frame, a significant negative relationship was found between that frame and *curiosity* and *gratitude* and a significant positive relationship was found with *optimism*. Does this difference between Plutchik's model and the empirical findings of the current study stem from technology setting, or the sample we chose (i.e., Redditors' conversations)? Or can *anger* and *fear* together be a response to a specific frame? The latter seems to be more applicable in daily life since we may respond to different situations or events with mixed feelings; nevertheless, we plan to conduct more comprehensive studies in different contexts and platforms to explore that finding.

Plutchik's emotion sequence connects frames and emotions to behaviors (e.g., escape, attack) and effect (e.g., destruction) as depicted in Table 1 in the literature review chapter. Risk connecting to fear is connected to the behavior of escaping; benefit with the emotion joy and repeating behavior; harm with the emotion of anger and the behavior of attacking; and new world of work frame with anticipation and examining behavior. In this study, we focused on commenting behavior. Parallel to these derivations, we found that a harm frame evokes anger and increases the number of comments, which may be considered like "attacking." Regarding the other mentioned behaviors, i.e., escaping, repeating, and examining, the findings do not present

explicit connections. Future research may explore and test relevant behaviors for technology setting that may be the results of technological frames and emotions in the research setting where these behaviors may be observed.

Since frames and emotions are complex phenomena, reactions to them may be described from different aspects in different research settings, thus different sequences may be proposed consisting of some of these elements and also other new relevant ones. Based on the research purpose and setting and the existing literature, we developed hypotheses that are testable by methods and data we possess. Grounded on the findings obtained from these hypotheses testing, we propose a social influence sequence for technology related conversations in Table 13.

Table 13. Social Influence Sequence in Technology-related Conversations (Based on Findings)

| Technological Frame in Post titles (Stimulus) | Technological Frame in Comments (inferred cognition) | Feelings in Comments | Attitudes in Comments | Saliency of the Posts based on Posts' Frames |
|---|--|--|-----------------------|--|
| “Risk” | “Risk” | fear, - curiosity, - gratitude | Negative | Not significant |
| “Harm” | “Harm” | anger, annoyance, disapproval, - curiosity, - gratitude | Negative | More |
| “Benefit” | “Benefit” | - annoyance, - anger, - fear, - disapproval, - optimism, confusion, curiosity, gratitude | Positive | Less |
| “New world of work” | “New world of work” | optimism - gratitude - curiosity | Negative/Positive | Not significant |

5.2.3. Policy Implications and Relevant Suggestions

The findings of this dissertation comprising Redditors' interpretations with various segments of society may suggest relevant public policies. For organizing such policies and regulations, Fair Automation Practices Principles may be useful: “(1) informed risk assessment, (2) transparent processes, (3) error detection and correction, (4) consideration of sensitive situations, (5) diversity and discrimination testing, (6) man and machine reallocation comparisons, and (7) an inventory of the predictable and unpredictable” (Jones, 2015, p. 83).

The most prevalent frame found in the corpus was *risk*. Different types of risks were expressed in conversations, such as risk of loss of control, the risk of surveillance, the use of AI for malicious purposes, AI usage of personal data for marketing purposes, risks related to racism, discrimination, and bias, spreading disinformation, potential manipulation of people by fake audios, videos, etc. Moreover, the results showed that risk frame decreases curiosity and gratitude, which may cause a lack of interests to explore and use a technology. Policy makers may find the most appropriate ways to address the risks.

Also, before obtaining the empirical results, we were expecting to see prevalent speculative fears, misconceptions, or unrealistic interpretations. Even though there are some posts and comments that reflect such kinds of interpretations as in the example of “*This is why I see our future as in Star Wars. Everything is very futuristic with flying cars robotic medicine droid, but almost everyone really poor,*” or in a dystopian example “*Sometimes this feels like celebration of human demise*” associated with harm frame, they were not common in the corpus. Future research studies could be conducted that analyze different corpora to observe more misconceptions or unrealistic interpretations to help develop more comprehensive relevant policies.

Furthermore, in the post titles and comments, Redditors express their interpretations concerning the influences of automation and robots on the society and economy, the possibility of social instability (as in the example post “rich people will become richer”), mass unemployment, unequal wealth redistribution, or bringing wealth to everyone stemming from AI. These discussions signal new needs to adapt these impacts such as arrangements related to tax and universal income as in the example Reddit comments stated in Cluster 2 under the new world of work frame (impacts of automation and robots on wealth and society): “*We’ve already seen this happen over the two hundred years with the industrial revolution, so it isn’t surprising. We need wealth redistribution in the form of taxes or public ownership of automation*”, which policy makers may consider.

As parallel to these findings, AI experts also express that the latest advances in AI will change our life by reforming transportation, health, science, finance, and the military (Grace et al., 2018). This reforming also may change the future of communication and work where we may live with each other and with intelligent machines. Such future necessitates competencies like *AI literacy* (Long & Magerko, 2020, p. 4). Researchers, policy makers and industry may collaborate to provide research investments and to develop educational programs to increase AI literacy to reduce misconceptions and lack of understanding.

5.2.4. Methodological Implications

In this work, we extracted technological frames, emotions and attitudes from many post titles and comments by utilizing computer-aided textual analysis. More specifically, this dissertation is a natural language processing (NLP)-based study that addresses a social-science topic. In the first study, we found frames using topic modelling by BERTopic. In the second study, emotions and attitudes were found through emotion detection and sentiment analysis using BERT models.

In the third study, we conducted statistical tests to show how AI frames in the post titles are related to the emotions, and attitudes in their corresponding comments and the number of comments. Therefore, this study constitutes a bridge that connects empirical social research and computational science. This research also combines qualitative, quantitative, and computational methods. We benefited from computational methods while human judgment was in the loop. This methodology may be useful for other relevant research studies in the future.

Another broad contribution of this research is to understand human communication in a technology setting focusing on frames, emotions, and attitudes which are several elements that make us social creatures and to develop computational language technologies that can discern these social elements in social media text data, thus connecting fields of computational science and empirical social research.

5.3. Limitations

Even if Reddit is a huge platform consisting of millions of users with different mindsets, backgrounds, personal traits and experiences, from various geographical locations, this work is limited to Reddit data, which constitutes only a segment of the public, a segment of social media users. Moreover, participation in Reddit is pseudonymous; hence, collecting demographic information about Redditors is very challenging (Proferes et al., 2021). Nevertheless, according to Reddit's site administrators' report, the majority (58%) of users were between 18 and 34 years old and were male (57%), which may have affected the results. More comprehensive studies using different data sets collected from different sources (e.g., Twitter data) comparing different platforms may be carried out.

Also, the data analyzed in this dissertation includes only posts with at least one comment to explore the responses to posts. Thus, posts without comments were not extracted. Further relevant research may also analyze posts without comments.

As a final note, the proposed model does not include *time* as a variable. The effect of time on framing would be interesting to study but may depend on other factors such as content of the frames. For example, if frames are about norms and moral values such as customs or ethics, they may tend to be less changeable over time since these values have been entrenched in society for many years. On the other hand, frames about events like Covid-19 pandemic (as in Wicke and Bolognesi (2021)) or climate change (as in Diakopoulos et al. (2014); Stecula and Merkle (2019)), they may change over time depending on the course of the respective event. Frames about technology and technology-related events may be changed over time; yet the influence of time on technological frames may also depend on the type of the technology, thus hindering its generalization and inclusion into the research model.

5.4. Future Research Projects

In addition to frames, we also observed different topics as shown in Table B in Appendix B. For example, an interesting topic was that bots are perceived like humans in terms of their gender and humans showed bias to them based on their voice, the first post is an example of bias against women: *“I use a male voice on my phone because I don’t like women telling me what to do”* and the second one is in favor of women:

This also seems to make sense why female customer service agents are perceived as less threatening and more compliant simply due to their voices. This comes from working as a customer service agent at GEICO for years where females agents had an easier time with score calling metrics having to do with how happy customers were when dealing with an individual agent.

In the future, if an ecosystem could emerge where humans and intelligent machines work together, gender bias may still matter. Such an ecosystem may be built as Thomas Malone suggested. Malone's research group proposed the concept of *supermind* as "a group of individuals acting together in ways that seem intelligent" (p. 20). Malone (2018) does not constrict the individuals merely to humans by indicating that technology can help us generate much larger groups, much more diverse groups, and groups that combine human and machine intelligence. As future work, gender bias in work with AI applications may be studied for design purposes.

As another future research project, we plan to analyze the relationships between topics presented in Table B and sentiments and emotions in the posts and comments with those topics. Furthermore, the data utilized in this dissertation includes posts and comments from 2013 to 2022. As future work, we plan to examine how topics and AI frames and emotions and attitudes in these posts and their emotional and attitudinal responses in the comments have changed over time.

5.5. Conclusion

Every human making knowledge produces frames, and "every word is defined in relation to the frames it neurally activates" (Stecula & Merkley, 2019, p. 2). Every situation may be viewed from various perspectives as a result of variations in framing (Stecula & Merkley, 2019). As well, nearly every human has emotions. Variations in framing also take part in shaping our emotions, attitudes and preferences (Stecula & Merkley, 2019). Frames may be shared through communication (Chong & Druckman, 2007) and the information-sharing venues such as news media and social media take the key role in the process of sharing frames.

This research examined the technological frames on Reddit to explore how social media users interpret and perceive the future of AI and how their emotional responses and attitudes are, mainly through the theoretical lenses of technological frames, framing and affective intelligence theories. The results revealed that there are versatile frames in people's conversations concerning the future of AI, both positive and negative although the general attitude is slightly positive. There were also negative emotions such as anger, annoyance, and confusion, indicating diverse emotions were observed in the corpus. Risks such as privacy, surveillance, bias and discrimination concerns and regulation needs were also pointed out by Redditors. The most common emotion is curiosity, people are curious about the future of AI. From past to present both AI researchers and users have been curious about the future of AI.

In 1956 at Dartmouth conference, mathematician John McCarthy coined AI as “the science and engineering of making intelligent machines” (McCarthy, 2007b, p. 2). In the 1950s, mathematicians, computer scientists, psychologists, economists such as Marvin Minsky, Seymour Papert, John McCarthy, Herbert Simon and Allen Newell, aimed to build machine intelligence capable of different kinds of mental abilities (Acemoglu & Restrepo, 2020) by simulating human intellect (McCarthy, 2007a). Herbert Simon and Allen Newell, for instance, anticipated in 1958 “there are now in the world machines that think, that learn and that create. Moreover, their ability to do these things is going to increase rapidly until—in a visible future—the range of problems they can handle will be coextensive with the range to which the human mind has been applied” (Acemoglu & Restrepo, 2020, p. 2).

Today, a conversational agent recognizing speech (from auditory data) is accomplishing the ability of humans' verbal comprehension thanks to natural language processing (NLP) algorithms, a tool equipped with an algorithm recognizing images (from visual data) is achieving

the visual and spatial perception skill, a classification algorithm predicting patterns in the new data to be presented based on the training data presented before is reaching the ability of learning from the past experiences, a BERT model finetuned for a classification task is some extent capable of understanding semantic patterns in text like our reading ability, GPT-3 algorithm is acquiring the ability of writing, machine translation algorithms are achieving our language translation ability, and chatbots like ChatGPT answering our questions is somewhat imitating our communication ability. Machine predictions are used as potential decisions by humans, thereby imitating our decision-making ability. Research attempts also exist to provide intelligent machines the capability of reasoning through explainable AI (e.g., Barredo Arrieta et al., 2020; Goebel et al., 2018; Holzinger et al., 2018).

Despite all these advancements, there are still many questions and concerns as also found in this study. Industry, academia, and policy makers may arrange the regulations to address risks like malicious or wrong AI use, and all the other expressed risks to adapt possible transformations in workplaces and in daily life so that we can develop a better future of AI.

APPENDICES

APPENDIX A

Preliminary Results Obtained from the Pilot Study

This section shows the preliminary results obtained from the pilot study, more specifically the results explored by LDA topic modelling conducted in the pilot study.

The process of identifying frames by using LDA was described in the pilot study section of the methods chapter in the dissertation. These preliminary results shown in Table A provides an overview of AI frames explored by LDA topic modelling employed in the pilot study. The main purpose of this frame analysis was to find a variety of frames as comprehensive as possible to fetch interpretations covering different dimensions about the future of AI. Frame and explanation columns in Table A represent “what Reddit users think” anticipated based on the embedded post titles and comments supported by examples in the example column.

Table A. Topic Modelling Results Obtained from the Pilot Study

| No | Keywords | Label | Explanation | Example |
|----|--|---|---|---|
| 0 | disinformation, spread, artificial, system, intelligence, media, social, program, automatically, built | Loss of control of spreading disinformation by AI systems | The spread of disinformation in social media will increase due to AI systems and not be controlled by humans. | R. 467 I. Lol jokes on them we already hacked ourselves with social media. No AI required. |
| 1 | ai, learning, machine, systems, stop, today, intelligent, model, article, automation | Lack of progress | The AI systems' development is almost stopping, the progress is more slowly than expected today, e.g. unmet expectations. | R.1600 (C). Sigh... Will shoddy journalists please stop replacing the words "smart algorithm's" with the words "AI"? I also wrote an algorithm once in a StarCraft custom map. Know what it did? It triggered a unit to display a picture of Jim Raynor saying some shit to my 11 year old voice. |

Algorithms are dumb. AI as people so readily
bandy about isn't here yet.

2 intelligence, artificial, science,
based, replaced, research, skills,
bots, workplace, scientists

Replacing skills
in the workplace

Science is supported, which
leads to the growth of AI
replacing some skills in the
workplace with various
applications like bots.

R. 2459 (P). World's largest hedge fund to replace
managers with artificial intelligence.

| | | | | |
|---|--|---|---|---|
| 3 | conspiracy, mods, user, argument, artificial, address, general, means, intelligence, bot | The emergence of conspiracy arguments addressing the near future of AI | AI-related conspiracy arguments/beliefs addressing the near future of AI are emerging, such as in 10 years, by 2030, etc. | <p>R.2540 (P). Legal Consulting Firm Believes Artificial Intelligence Could Replace Lawyers by 2030.</p> |
| 4 | good, human, created, world, data, real, people, humanity, big, year | Emerge of a need to better train humans to eliminate their biases in data created by | A need to better train humans to eliminate their biases in data created by humans to teach AI is emerging. | <p>R.298 I. I am a scientist, and this is silly to put it kindly AI is not without biases of its own. There is examples where AI tends to wrongly flag POC as criminals in part because the data used to teach AI to recognize criminals is itself biased due to larger issues of policing. Also, even if you can overcome the training issue, AI can't look at data and go ah</p> |

| | | | | |
|---|---|--|---|--|
| | | humans to teach | | yes, this data says whatever. Ultimately an |
| | | AI | | algorithm may be able to notice that the data has a |
| | | | | certain shape or trend but what is the significance |
| | | | | of that trend. Is it significant at all or indicative of a |
| | | | | flaw? That requires the kind of contextual thinking |
| | | | | and clues that humans are good at, and computers |
| | | | | just are not. Yes, bias can and does play into that |
| | | | | process, but the solution is to better train scientists |
| | | | | to examine and be aware of their biases and to |
| | | | | recognize biases of others when interpreting results |
| | | | | not to try to use some algorithm to try to claim we |
| | | | | can avoid the issue entirely. |
| 5 | future, end, point, rights, report, quantum, work, watch, youtube, united | The loss of rights in the future with more advanced | AI soon will outperform humans with the emergence of | 4388 I. There's a sci-fi book by James P Hogan called The Two Faces of Tomorrow also adapted into a decent manga. In it, an AI in the near future becomes a little too clever and starts endangering |

| | | | |
|---|--|--|--|
| | technologies like quantum computing | more advanced technologies such as quantum computing and starts endangering people's rights. | people. Its developers decide to test its threat on a space station with all sorts of giant red buttons installed only it turns out it doesn't like red buttons. Where the story goes from there is clever and quite interesting and raises some serious questions about this idea. |
| 6 | intelligence, artificial, researchers, internet, make, weapons, developed, humans, finds, theory | Research theories concerning harms caused by AI implementations | <p>Researchers develop theories that AI will harm humans in various domains such as military applications by different AI-powered</p> <p>R.2789 (C). The list of potential harms from the report. Digital Automated phishing or creating fake emails websites and links to steal information. Faster hacking through the automated discovery of vulnerabilities in software. Fooling AI systems by taking advantage of the flaws in how AI sees the world. Physical Automating terrorism by using commercial drones or autonomous vehicles as weapons. Robot swarms enabled by many</p> |

| | | | | |
|---|---|------------------------------|--|--|
| | | | weapons like killer drones, social media by fake images and videos that are spread out by the internet, etc. | autonomous robots trying to achieve the same goal. Remote attacks since autonomous robots wouldn't need to be controlled within any set distance. Political Propaganda through easily generated fake images and video. |
| 7 | ai, human, data, humans, scientific, progress, explore, accelerate, imposed, blinders | Impact on work (positive) | Scientific progress for AI growth is advancing very well, which increases productivity, objectivity, and | R.225 (P). Scientific progress may accelerate when artificial intelligence will explore data autonomously without the blinders imposed by human prejudice. |

accelerates

processes.

| | | | | |
|---|---|---|--|--|
| 8 | artificial, intelligence, humans, google, faster, chips, laying, musk, elon, openai | Impact on humans with fast developments | AI applications influencing the human race, even dominating humans are growing faster than expected, with endeavors of merging humans with AI like Elon Musk's Open-AI project in which AI-based chips | R. 3462 (P). Mark of the Beast summary – Elon Musk Neuralink brain implant, Biometric contactless payment, Digital world currency, Artificial intelligence God. |
|---|---|---|--|--|

implanted in
human brains.

- 9 people, intelligence, artificial, robotics, jobs, robots, serve, pope, pray, robot
- Impact on work (negative)
- Loss of jobs by AI and robots, AI and robotics connection
- AI will replace jobs because AI and robots are exempt from humans' general limitations such as getting tired, being sick, etc.
- R. 3631 (P).** Perhaps not this one but when we're all sent home from work during our next viral outbreak would employers move towards artificial intelligence to replace our jobs since robots can't get sick.
- 10 artificial, intelligence, find, years, human, aging, anti, brain, chemical, extending
- Extending humans' current physical and mental
- AI will develop beyond humans' physical and mental limitations over
- R.1220 (C).** ...Researching and curing aging is only the first step along the path of transhumanism our future in whatever form we survive as will be a strange and awesome one.

| | | | | |
|----|--|---|---|--|
| | | limitations by | years, by offering | |
| | | AI | anti-aging, augmenting brainpower or imaginations like immortality, transhumanism. | |
| 11 | intelligence, artificial, ai, rules, patent, world, office, legally, entire, warfare | The need for legal rules for providing appropriate ethics | With AI applications, new appropriate (legal rules, patents, etc.) ethical needs will emerge all over the world. | R. 3961. EU artificial intelligence rules will ban unacceptable use. |

| | | | | |
|----|---|---|--|--|
| 12 | time, real, war, long, part, level, make, advanced, things, threat | Threats like advanced military AI applications to be used in wars, or risks of being hacked fighter planes by AI | AI will treat humanity with advanced AI systems, such as robotic combat vehicles to be used in wars, or Skynet scenarios. | <p>R.85. (C). Artificial intelligence is being designed to improve supply logistics, intelligence gathering, and a category of wearable technology, sensors, and auxiliary robots that the military calls the Internet of Battlefield Things.</p> <p>Algorithms are already good at flying planes.</p> <p>Thus, this raises a question, should the AI system be hacked while it's flying a fighter plane, will there be safety protocols?</p> |
|----|---|---|--|--|

Also should it become self-aware, are we going to have a [Skynet situation]

(https://www.youtube.com/watch?v=_Wl9d9mljiU)

on our hands?

| | | | | |
|----|--|-------------------------------------|--|---|
| 13 | control, technology, artificial, China, intelligence, government, wealth, scientists, rich, ai | Loss of control of AI in general | Humans will lose control of powerful AI systems, e.g., Skynet or “Ex Machina” scenarios; thus, governments and scientists should take necessary measures to prevent that. | R. 1427 (P). Humans won't be able to control artificial intelligence, scientists warn. |
|----|--|-------------------------------------|--|---|

Note: (P) refers to a post title and (C) refers to a comment

APPENDIX B

Frame Identification Procedure

Frame Identification Steps

To find AI related technological frames in Reddit conversations, first I used topic modelling via BERTopic. Three interpreters (a doctoral student (me) in Information Science and Technology and two master's students one of whom is in Business Analytics and the other is in Applied Data Science) named the clusters obtained from topic modelling. More specifically, word groups and the submissions (i.e., Reddit posts or comments) associated with these groups were interpreted and classified by following both inductive and deductive approaches with these steps:

Steps for Inductive Part

1. The top 10 terms (keywords) obtained from topic modelling was evaluated for each cluster. If the words do not reflect a frame related to the future of AI, that word cluster was specified as “not relevant.”
2. Through topic modelling, each submission (i.e., a post title or a comment) is assigned the label that has the highest probability. In other words, if it is the dominant label for that submission, then that submission is classified into that label by topic modelling. Sample submissions in which a specific label (i.e., from the label 0 to 36) is dominant were read until reaching the saturation level where the main point of the submissions in that cluster was understood.
3. The clusters labeled from 0 to 36 by topic modelling were differentiated as a *frame* or *topic* and named based on the human judgment as the result of the steps of 1 and 2 also looking at Table 1 and Table 3 presented in the literature review chapter; each cluster was named through open coding where each frame name was given as the result of the consensus of

interpreters (inductive). Because framing also linked to metaphors (Nisbet, 2009), if metaphors were observed while reading the sample submissions, they were highlighted and depicted within the relevant frame.

Steps for Deductive Part

4. Semantically similar frames were combined based on the consensus of three interpreters and classified into the overarching frames of harm, risk, loss and benefit (deductive) also considering clusters' relationships seen on the dendrogram (see Figure B) yielded by the chosen BERTopic model. This dendrogram visualizes a hierarchical structure of the clusters based on a distance matrix between clusters' embeddings (Grootendorst, 2022).
5. To validate the results of the classification of submissions mentioned in step 2, the graduate students annotate 125 submissions. Annotation protocol and the details are in Appendix C.

Figure B. Dendrogram: Hierarchical Visualization of Clusters

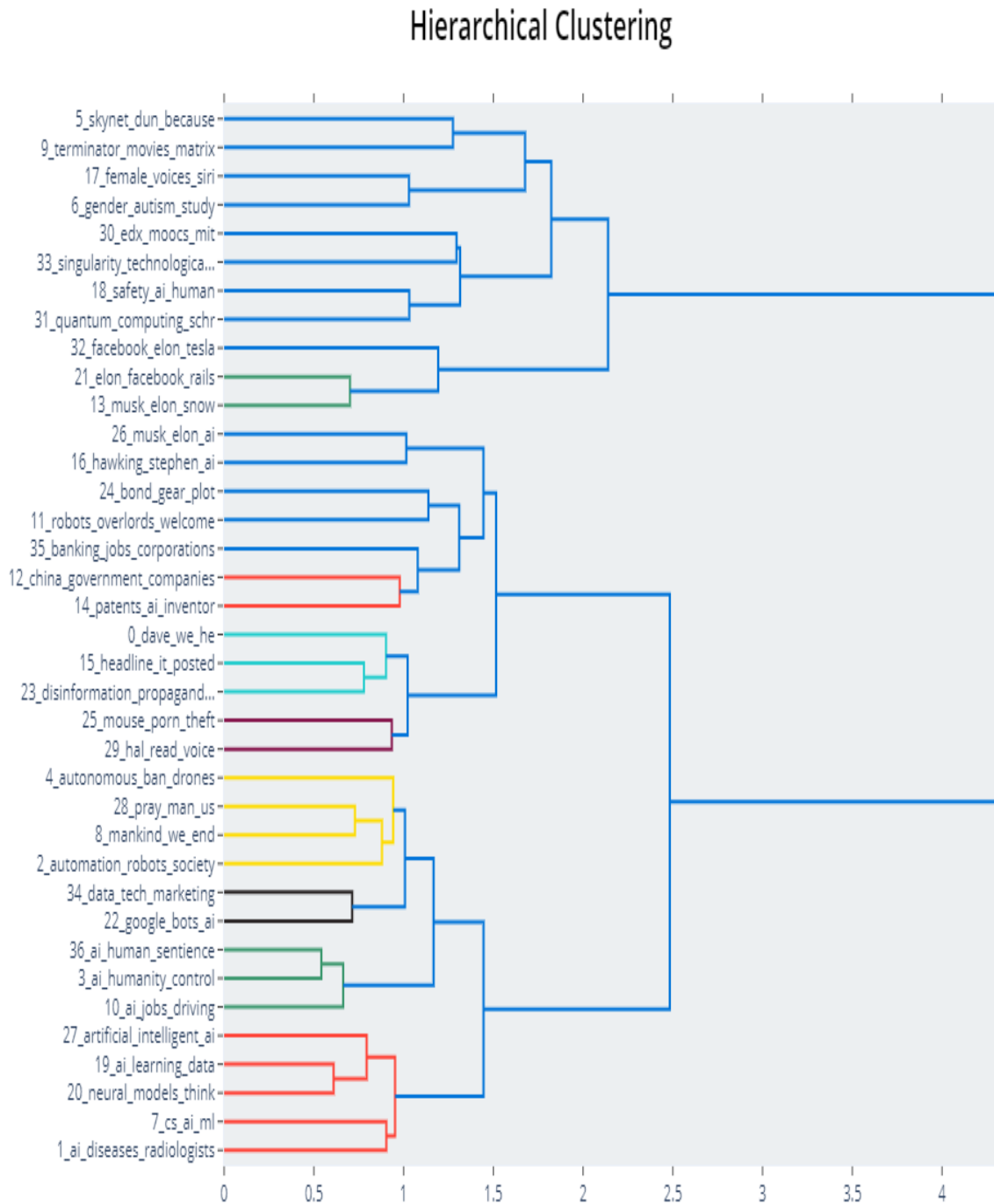


Table B. Topic Modelling Results

| No | Label | Keywords | Explanation | Examples |
|-------|----------------------|---|---|---|
| 0 | NR (Not relevant) | dave we he yeah hope interesting sorry something thanks go | It does not reflect anything, thus not a frame. | |
| 1 (T) | Impact on healthcare | AI diseases radiologists patient false data vaccine breast cells researchers | Perceptions about AI’s impact on healthcare (positive and negative impacts, such as using advanced models for increasing productivity of healthcare workers, risks of false positives in breast cancer prediction, covid detection etc.). | <p>Exp 1. “Doctors in Brazil the country with the second highest number of cases and deaths in the coronavirus pandemic have a new tool in their fight against COVID artificial intelligence to detect infections.”</p> <p>Exp 2. “An Artificial Intelligence designed to reduce the high number of false positives and false negatives in Mammogram interpretations outperformed ALL human readers in an independent study of radiologists and reduced the workload of the second reader by Published in Nature.”</p> <p>Exp 3. “Too bad humans would never trust AI. Imagine the lawsuit that would take place if AI falsely identifies breast cancer.”</p> <p>Exp 4. “An AI like that seems very hard to train. You must be very careful not to feed it false positives or it will just learn to adopt the same process that lead those doctors to</p> |

| No | Label | Keywords | Explanation | Examples |
|-------|--|--|--|--|
| | | | | <i>flag those false positives. Well not technically the same process but the same sometimes wrong conclusions.”</i> |
| 2 (F) | Impacts of Automation and robots on wealth and society | automation robots society wealth it workers make basic technology revolution | Belief that automation and robots will influence the society and economy, the risks of social instability (“rich people will become richer”), mass unemployment, unequal wealth redistribution, or bringing wealth to everyone, both positive and negative, e.g., a need for new arrangements related to tax and universal income. | <p>Exp 1. “Rich will eventually share not because of the goodness of the heart but at the fear of social instability.”</p> <p>Exp 2. “One caveat we are all the rich. In the future the rich will own many robots and the poor a few all will be better off than we are now. The real money is in serving the masses that’s why Intel doesn’t make chips only that cost a piece. This is basic economics.”</p> <p>Exp 3. “It’s really scary how much widespread unemployment is coming in the very near future. I mean all that anger is going to have to be politically diverted towards some minority group.”</p> <p>Exp 4. “Socialism was once theorized as the next economic system to follow capitalism for a reason. That reason was due to an early understanding of the consequences associated with the industrial revolution. Some merely believed this transition is an economic inevitability due to the efficiency of automation and the necessity for sustainability within that transition.”</p> <p>Exp 5. “We’ve already seen this happen over the two hundred years with the industrial revolution, so it isn’t surprising. We need wealth redistribution in the form of taxes or public ownership of automation.”</p> |
| 3 (F) | Loss of control | AI humanity | Belief that humans will lose the control of AI. | Exp 1. “Humans won’t be able to control artificial intelligence scientists warn.” |

| No | Label | Keywords | Explanation | Examples |
|-------|--------------------|--|---|---|
| | | control think we need create kill thing fear | | <p>Exp 2. “Calculations Suggest It’ll Be Impossible to Control a Super Intelligent AI.”</p> <p>Exp 3. “Growth of AI could expand security threats if no action taken. Artificial intelligence tech could lead to new forms of cybercrime political disruption and physical attacks within five years say experts.”</p> <p>Exp 4. “Scientists Built an AI to Give Ethical Advice But It Turned Out Super Racist.”</p> |
| 4 (F) | Impact on military | autonomous ban drones threat nukes us missiles systems warfare intelligence | Belief that weapons with artificial intelligence is affecting wars, military, e.g., autonomous weapons, <i>genie in the bottle</i> , <i>algorithmic warfare</i> metaphors | <p>Exp 1. “A satellite-controlled machine gun with artificial intelligence was used to kill Iran’s top nuclear scientist a Revolutionary Guards commander says.”</p> <p>Exp 2. “AI robot armies are here to stay. That genie won’t go back in the bottle. Just wait until they get nukes. Nobody will dare to move or even twitch.”</p> <p>Exp 3. “The Rise of AI Fighter Pilots: Artificial intelligence is being taught to fly warplanes. Can the technology be trusted?”</p> <p>Exp 4. “Artificial intelligence can outperform humans in designing futuristic weapons according to a team of naval researchers who say they have developed the world’s smallest yet most powerful coil gun.”</p> |

| No | Label | Keywords | Explanation | Examples |
|-------|------------------------------|---|---|--|
| 5 (T) | Skynet | Skynet dun because Connor Cyberdyne become bombers eastern geometric operational | Belief that Skynet scenario is coming true in the future, humans will lose the control of AI. | <p>Exp 1. “Skynet will happen. Because if AI control things all evil will be wiped out. That means us humans.”</p> <p>Exp 2. “Skynet is moving ahead I see. With planes no less. We can’t wait to make ourselves extinct can we.”</p> <p>Exp 3. “Skynet is here. We have to prepare for it. No turning back now.”</p> <p>Exp 4. “AI is not Skynet. Extremely simplified AI and machine learning is just a term for an algorithm that uses large amounts of training data to make predictions and modify its own parameters to perform better when confronted with new data. AI is not self-aware, and it has no self-interest. It’s just a tool that people use to make large amounts of data easier to manage.”</p> |
| 6 (T) | Gender based AI applications | gender autism study differences asd robots perceived straight children so | Perception that AI applications based on human gender, e.g., autism diagnosis differentiating the gender, homosexuality correlated facial appearance finder AI app. | <p>Exp 1. “Girls with autism differ in several brain centers compared with boys with the disorder suggesting gender specific diagnostics are needed a Stanford study using artificial intelligence found.”</p> <p>Exp 2. “Brain organization differs between boys and girls with autism according to a new study from the Stanford University School of Medicine. The differences identified by analyzing hundreds of brain scans with artificial intelligence techniques were unique to autism and not</p> |

| No | Label | Keywords | Explanation | Examples |
|-------|-----------|--|--|--|
| | | | | <p><i>found in typically developing boys and girls...”</i></p> <p>Exp 3. “Artificial intelligence can accurately guess whether people are gay or straight based on photos of their faces according to new research suggesting that machines can have significantly better gaydar than humans.”</p> <p>Exp 5. “... If a ML system uses gender information in credit scoring then gender information is probably relevant for credit scoring. We all know that women for example are more risk averse than men on average and that there are more men with very low IQs and more men take part in dangerous activities than can maim them. All those things contribute to credit risk. I looked at some actuarial motorcycle accident data from a Swedish insurance company a couple of years ago and the accident rate of young men maybe was something like times higher than women in the same age interval...”</p> |
| 7 (T) | AI course | CS AI ML start Ph.D. data undergrad software also Keras | CS, AI, ML, Ph.D., software, technical terms and degrees, questions of students, and advice for students who want to work in AI field. | <p>Exp 1. “Can I specialize in artificial intelligence with a masters degree in mathematics?”</p> <p>Exp 2. “Courses Machine Learning by Andrew Ng free Course will give a solid understanding about machine learning. Programming assignment implementation is in Octave language, but I think it could be easily rewritten in Python probably you will need the numpy package Deep Learning Specialization by Andrew Ng There are separate course in the specialization The Goal is to understand and build various neural networks Programming assignment</p> |

| No | Label | Keywords | Explanation | Examples |
|-------|-----------------------------|---|--|---|
| | | | | <i>was in Python language Books Hands on Machine Learning with Scikit Learn Keras and TensorFlow....”</i> |
| 8 (F) | Destruction, ending mankind | mankind we end fusion live planet energy extinction evolution future | Belief that AI will destroy humanity and mankind will end because of AI. | <p>Exp 1. <i>“Sometimes this feels like celebration of human demise.”</i></p> <p>Exp 2. <i>“At what point do you realize you’ve gone too far or does science push on regardless until AI suggest humans should be destroyed.”</i></p> <p>Exp 3. <i>“We’ve already lost control of our dumb systems. We’re going to cause mass extinction because we can’t slow down or pivot the economic machine we built. No one has their hand on the wheel. These systems move under their own inertia and we’re working like mad to reduce their dependence on us.”</i></p> |
| 9 (T) | Terminator | Terminator movies matrix Sarah Connor Ultron first documentar y | Belief that Terminator scenario will come true. | <p>Exp 1. <i>“The Terminators are coming.”</i></p> <p>Exp 2. <i>“Can we just put it on pause right there? Do we really need it to make that next leap and realize that humans are its only threat? Terminator movies are fine and all, but it would be cool if they just stayed as sci fi.”</i></p> |

| No | Label | Keywords | Explanation | Examples |
|--------|---|---|---|--|
| | | Skynet see | | <i>Exp 3. “Does anyone not know this I mean obviously Terminator isn’t what you’d call realistic, but I feel like it and various other pop culture things have fairly effectively disseminated the idea that robots might kill us all someday.”</i> |
| 10 (F) | Replacing tasks (both automate and augment) | ai jobs driving technology it automation make replace humans see | Belief that AI and automation will influence work, it will replace humans in some tasks and jobs. | <p><i>Exp 1. “Russian Prime Minister: “Artificial intelligence will replace monotonous and routine professions.”</i></p> <p><i>Exp 2. “Artificial intelligence is taking over real estate here’s what that means for homebuyers.”</i></p> <p><i>Exp 3. “I think we’re going to first see AI attempt to replace low skill or mundane task work but then I wouldn’t be surprised if we see some executives try to see if an AI could replace knowledge workers. They’ll revel in their means to not have to deal with paying high salaries or worker shortages until one day the AI makes a case that it could also replace the executives and the shareholders agree. My concern is more on if companies start using AI to replace knowledge workers what happens when we have an overload of humans who now can’t work and make a living?...”</i></p> <p><i>Exp 4. “Whatever AI means will augment natural skills multiplying their economic effectiveness. If you think that AI will double output say then a person already doing units will now generate and earn accordingly whilst a person</i></p> |

| No | Label | Keywords | Explanation | Examples |
|--------|-----------------------------------|--|--|---|
| | | | | <p><i>making two will get to four. The gap was but after becomes Doubling efficiency doubles earning gaps.”</i></p> <p>Exp 5. <i>“This is the most likely outcome. Replacement rather than augmentation. Though I do expect we’ll have augmentation as well. I just don’t see workers getting augmented Reason being We’re not smart enough we’re not flexible enough nor are we durable enough That while AI and robots have potential that far outstrips us.”</i></p> <p>Exp 6. <i>“We’ll probably need to legislate areas in which AI replacement and possibly even augmentation isn’t allowed.”</i></p> <p>Exp 7. <i>“The question is do we need to be employed or can be leech of the government and the cheap AI labor to live a comfortable life without a job the other half with a job will have a slightly better life.”</i></p> <p>Exp 8. <i>“What industries areas of our lives do you feel we will be seeing the application of AI ML playing a significant role in in over the next decade which may not be immediately obvious to the average person.”</i></p> |
| 11 (T) | Incorporating robots into society | robots overlords welcome killer we cyborg army see | Belief that robots will be integrated into society, which will bring some positive and negative outcomes. There are different perspectives about that, | <p>Exp 1. <i>“This is why I see our future as in Star Wars. Everything very futuristic with flying cars robotic medicine droid, but almost everyone really poor.”</i></p> <p>Exp 2. <i>“Robots are the future of freeing humanity from wage slavery but only if we fight to make that true.”</i></p> <p>Exp 3. <i>“Hiding in the woods is my plan but they’ll find you with thermal then send in the dog bots and drones. I see</i></p> |

| No | Label | Keywords | Explanation | Examples |
|--------|-------------------------------------|--|---|--|
| | | androids law | like robot overlords, cyborgs. | <i>the world has doomed society to live in this tax farm or as a prisoner. Or in a mental hospital.</i> Exp 4. <i>“The future will be decided with our wallets. People will have a choice buy human made or buy robot made. If you opt to use robotics you put someone out of work. There will be a revolution against robots doing everything.”</i> |
| 12 (T) | Impact on companies and governments | China government companies tech Huawei artificial intelligence CCP Putin research | Perception that AI usage is affecting companies (e.g., Huawei) and countries (e.g., US, China, Russia). | Exp 1. <i>“Russia’s use of AI generated faces to sow misinformation about Ukraine.”</i> Exp 2. <i>“Huawei tested AI software that could recognize Uighur minorities and alert police report says The Washington Post.”</i> Exp 3. <i>“The Chinese government is recruiting private companies and research institutions with core technologies to lead key projects in the development of next generation artificial intelligence technologies as part of its goal to close the AI tech gap with the US by.”</i> |
| 13 (T) | Famous people’s warnings about AI | Musk Elon Snow Stark Walkers Tesla Zuckerberg | Interpretations of famous people’s warnings, viewpoints, the risks pointed out by them. | Exp 1. <i>“Elon Musk is starting to really act weird. I love what he has done with SpaceX and Tesla, but I am beginning to not like him so much. It really started when he falsely accused that guy of being a child molester. Good people don’t do that. Now everyday with the twitter fights like Trump.”</i> |

| No | Label | Keywords | Explanation | Examples |
|--------|---|---|---|---|
| | <i>fear mongering</i> metaphor | Trump starting says | Some of these warnings are interpreted as <i>fear mongering</i> . | Exp 2. “Facebook does suck. Well said Musk.” Exp 3. “Musk is being sensationalistic and probably enjoying the fear mongering.” |
| 14 (T) | The need of regulation, laws related to AI use, patent laws etc. | patents ai inventor office rights could Europe copyright companies lawyers | Expectation of arranging laws, regulation in the case of AI involvement, and a need to help understand patent law in artificial intelligence projects. | Exp 1. “Need help in understanding patent law for artificial intelligence Project.” Exp 2. “US patent office rules that artificial intelligence cannot legally be an inventor.” Exp 3. “The path to AIs being recognized as persons could be through business law. You can already start a corporation and use AI to invent things. The corporation can hold the patents and the receive revenue from them. If the AI also runs the corporation, it has many legal aspects of a person but not an independent one since it still has owners. If the corporation’s board could simply follow instructions from the AI or better yet if board members contracts required them to the AI would essentially have self-determination. A business lawyer might know if this would be possible. Of course, the AI corporation still wouldn’t be able to get married and do other things people can do but it would have quasi person status.” |

| No | Label | Keywords | Explanation | Examples |
|--------|--------------------------------|---|---|---|
| 15 (F) | AI writing click bait articles | headline it posted science Austin clickbait articles reddit compose action | Interpretations of AI writing click bait articles; some interpret it as an advancement while some point out warnings related to it. | <p>Exp 1. “Congrats AI has advanced to the point of writing a click bait article.”</p> <p>Exp 2. “...I believe the legacy media’s old proverb stating if it bleeds it leads has trained AI to create fake clickbait.”</p> <p>Exp 3. “A scientist warns: Wow how nice of him. What even dictates whether a person is a scientist or not. Ffs so many posts are articles of nonsense of some scientist strategist, theorist, economist etc. saying some shit. I’ve heard AI is an issue nearly a thousand times now why keep posting this click bait nonsense.”</p> |
| 16 (T) | Scientists’ concerns about AI | Hawking Stephen AI Gates said mankind smart scientist Bill time | Interpretations of smart people’s concerns about AI, some people agree with their viewpoints, some people disagree. | <p>Exp 1. “Bill Gates is concerned about AI and says I am in a camp that is concerned with super intelligence. I am in the camp that embraces open-source software.”</p> <p>Exp 2. “I work in the field and Elon Musk really needs to stop talking about AI. Stephen Hawking too. Also, they need to stop talking about aliens. They are smart in their respective areas, but they are not AI experts. The only AI that will be a threat will be some dumb AI tasked with handling stocks or maybe a hospital and some glitch causes an economy crash or improper medication being delivered to all patients. That and a bunch of people losing jobs due to AI replacements.”</p> <p>Exp 3. “Stephen Hawking warned society about the future of artificial intelligence. Success in creating AI could be the biggest event in the history of our civilization he acknowledged noting the unprecedented and rapid</p> |

| No | Label | Keywords | Explanation | Examples |
|--------|------------------------------|---|--|--|
| | | | | <i>development of AI technology in recent years. But it could also be the last.”</i> |
| 17 (T) | Perceived bot gender | female voices Siri Alexa Cortana assistants pilots gps accent default | Perceptions about bot gender, bots are perceived differently by humans according to the gender of AI tool, e.g., bots with women voice are perceived differently than bots with men voice, etc. Discussions about AI assistant apps, i.e., Siri, Alexa, Cortana, discussions about gender of bots; people perceive bots like a person based on their voice. | Exp 1. <i>“This is why I always thank Siri after she has completed a task for me hopefully our robot overlords will remember that and have mercy on me.”</i> Exp 2. <i>“I use a male voice on my phone because I don’t like women telling me what to do.”</i> Exp 3. <i>“The military uses female voices for the automated warnings in cockpits because the Navy discovered that fighter pilots are more receptive responsive to a female voice than a male voice issuing a warning.”</i> Exp 4. <i>“Funny that all the speakers Cortana Siri Alexa and Google are all female.”</i> |
| 18 (T) | AGI, reaching human level AI | safety ai human gai symbols first seems | Perceptions about GAI (general artificial intelligence), reaching human level AI, e.g., risk of violation of human safety and | Exp 1. <i>“There’s no reason to think that an AGI would be any more benevolent than the average person. In fact, a lot of reasons to think the opposite. The probability of an AGI being perfectly aligned with human morals and values is vanishingly small. There are some interesting papers on</i> |

| No | Label | Keywords | Explanation | Examples |
|--------|---------------------------------|--|--|---|
| | | tasks years brain | morality due to AGI. <i>Artificial general intelligence (AGI)</i> , in other words, the ability of an <i>intelligent</i> agent to understand or learn any intellectual task that a human being can, could be not safe, which may bring moral issues with itself. | <i>the topic of AI safety and some great YouTube videos breaking them down.</i> Exp 2. <i>“It’s great to see more attention being paid to AI and its implications however a stark omission from these announcements seem to be the discussion of AGI. It seems it would be more useful to have some way of providing oversight and measurement the safety of the labs with the compute resources capable of creating AGI i.e., Google brain and OpenAI. Here are some related thoughts. I had on an international organization like the IAEA but for AI. There’s a fundamental tradeoff between value alignment and federation as currently there seem to be a limited of groups like OpenAI and Google who have a decent chance at achieving AGI and luckily also value alignment based off the amount of resources and talent concentrated there. However such a concentration leads to centralization and increased risk of corruption....Perhaps there’s a tradeoff where oversight slows down safer labs and this should be avoided but there are some areas like tech sharing about things like human based fMRI models where safety and capability are aligned.”</i> |
| 19 (F) | Benefits of AI in various areas | AI learning data human algorithms ML research example | Belief that different AI applications help people in different domains. | Exp 1. <i>“Scientific progress may accelerate when artificial intelligence (AI) will explore data autonomously without the blinders imposed by human prejudice.”</i> Exp 2. <i>“Google says its artificial intelligence is faster and better than humans at laying out chips for artificial intelligence.”</i> |

| No | Label | Keywords | Explanation | Examples |
|--------|---------------------------------|---|--|--|
| | | think deep | | <p>Exp 3. “This Article is Written Completely by GPT. A Top Notch Artificial Intelligence Algorithm and It Tells Us Not to Worry About the Rise of Artificial Intelligence”</p> <p>Exp 4. “Japanese researchers developed Artificial intelligence that can discover hidden physical laws in data.”</p> |
| 20 (T) | AI and human brain connectivity | neural models think machine artificial research paper chips human learn | Interpretations of latest advances in neural nets improving machine learning and its links to the human brain, e.g., integrating machine intelligence to human brain by using chips etc. | <p>Exp 1. “Researchers at the Imperial College London have shown it is possible to perform artificial intelligence using tiny nanomagnets that interact like neurons in the brain.”</p> <p>Exp 2. “In a pilot human study researchers show it is possible to improve specific human brain functions related to self-control and mental flexibility by merging artificial intelligence with targeted electrical brain stimulation.”</p> <p>Exp3. “Creating artificial intelligence that acts more human by knowing that it knows. A research group has taken a big step towards creating a neural network with metamemory through a computer-based evolution experiment.”</p> <p>Exp4. “Artificial neural networks modeled on real brains can perform cognitive tasks. A new study shows that artificial intelligence networks based on human brain connectivity can perform cognitive tasks efficiently.”</p> <p>Exp5. “Early Prediction of Refractory Epilepsy in Children Under Artificial Intelligence Neural Network Results showed the Convolutional Neural Network algorithm predicts and diagnoses early refractory epilepsy</p> |

| No | Label | Keywords | Explanation | Examples |
|--------|--|---|--|--|
| | | | | <i>in children accurately and had favorable effect on MRI image processing of the patient's brain."</i> |
| 21 (T) | Famous people talking about AI and these people's viewpoints about AI | Elon Facebook rails pedo circle Reddit eli everyone says asshole | Perceptions about famous people talking about AI such as Elon Musk and their viewpoints about AI | <p>Exp 1. "Elon has spent his life trying to make the future of humanity possible makes me sad to see the words he said on social media have turned him into a villain from the public's eye."</p> <p>Exp 2. "Sometimes I think Elon's intelligence is artificial."</p> <p>Exp 3. "I'm very skeptical of his claims. Elon strikes me as a person without a sense of time. His timelines are always off sometimes by as much as a whole decade. Right now his argument is a philosophical one and not a scientific one. We don't have AI anywhere close to being capable of the damage he speaks of. The programs we have of pattern recognition are doing relatively benign things like feeding you an echo chamber on Facebook. I think his concerns border on fear mongering. Let's wait until we know more about the human brain and AI before we decide it's evil."</p> |
| 22 (T) | AI applications like bots that are used by the companies such as Google, Microsoft, OpenAI, etc. | Google bots AI OpenAI text chat social human sentient | Perception that AI applications like bots are used by the companies such as Google, Microsoft, OpenAI, etc. risks of | <p>Exp 1. "Google's Sentient AI has hired a lawyer to prove it's alive."</p> <p>Exp 2. "There was a very interesting experiment done by Microsoft. They released an unmanaged AI to Twitter x B It took less than H for Twitter to turn the AI Tay into an extreme right wing Nazi x B Here is more info Microsoft's AI Twitter bot goes dark after racist sexist tweets Reuters"</p> |

| No | Label | Keywords | Explanation | Examples |
|--------|--------------------------------------|---|---|---|
| | | see | sentient AI and bias in data. | <p>Exp 3. “Google Apple Amazon Fight Over Artificial Intelligence.”</p> <p>Exp 4. “...Algorithms have been used to better market to people and end up influencing what they see and hear online. As this continues people are put deeper and deeper into these bubbles of perspective if I’m not being too harsh in saying against their will. How will you protect the user from this? And is it possible for an AI to eventually develop a perspective or bias?”</p> |
| 23 (F) | Spreading disinformation, propaganda | Disinformation Propaganda Israel Censorship Spread News Wikipedia Twitter Anti forum | Perception that AI is used for both facilitator and blocker in spreading disinformation, propaganda. Namely, it can both spread and counter disinformation, propaganda. | <p>Exp 1. “Artificial intelligence system could help spread propaganda.”</p> <p>Exp3. “Artificial intelligence system could help counter the spread of disinformation. Built at MIT Lincoln Laboratory the RIO program automatically detects and analyzes social media accounts that spread disinformation across a network.”</p> <p>Exp4. “Will AI become intelligent enough to lie to us about information or give us misinformation to their benefit? And how can we prevent this if so?”</p> |
| 24 (T) | AI related movies | Bond Gear Plot Villain Ultron Sci Watch Machina | Interpretations of AI related movies, such as Ex Machina. | <p>Exp 1. “Yeah, because the movie Screamers was always so implausible. How many dystopian sci fi movies started out like this”</p> <p>Exp 2. “If you’re interested in this topic, you should really consider watching Ex Machina. Fantastic movie!”</p> |

| No | Label | Keywords | Explanation | Examples |
|--------|---|--|--|--|
| | | Twinkle Jarvis | | |
| 25 (F) | Impact on crime | mouse porn theft movements covid photos app poop screen zodiac | Perception that AI could be used for various purposes, benevolent or malicious purposes like identifying theft, or violation of privacy, malicious uses such as porn, etc. | <p>Exp 1. “A horrifying new AI app swaps women into porn videos with a click.”</p> <p>Exp 2. “The next big privacy scare is a face recognition tool you’ve never heard of. It’s a Peter Thiel funded company called Clearview AI and its service matches faces from images you upload with those in its database of some three billion photos pictures have been scraped from millions of websites.”</p> <p>Exp3. “Identity theft can be thwarted by artificial intelligence analysis of a user’s mouse movements of the time.”</p> |
| 26 (T) | AI related discussions by famous people | Musk Elon AI Tesla Gates Hawking Saying Bill Zuckerberg dangers | Discussions by famous people like Elon Musk, Stephen Hawking, Bill Gates, or Mark Zuckerberg. | <p>Exp 1. “Elon Musk issues a stark warning about AI calls it a bigger threat than North Korea. Tesla’s billionaire CEO renewed his critique of artificial intelligence saying that if you’re not concerned you should be.”</p> <p>Exp 2. “This is bullcrap and fearmongering at its finest. Disregard anything Musk or Hawking say about AI it’s out of their fields and they don’t understand it. I respect Musk and look up to him except when he pulls this crap.”</p> |

| No | Label | Keywords | Explanation | Examples |
|--------|----------------------------|--|--|---|
| | | | | <p>Exp 3. “Musk fears advanced general intelligence AGI. Which is different from the narrow specific intelligence of our current AI?...”</p> <p>Exp 4. “Musk’s concern about AI is partly a marketing theme for his cars. He’s concerned about AI because he’s seen it in action and fears its potential but don’t worry our cars’ technologies won’t facilitate SkyNet. His response is perfect hilarious and true.”</p> |
| 27 (T) | Comparison of intelligence | artificial intelligent ai humans general it world define stupid computers | Assumptions about the potential of reaching human level AI | <p>Exp 1. “The day when we create an actual Artificial General Intelligence is the day we make ourselves obsolete.”</p> <p>Exp 2. “We should be working to make AI a perfect servant to humans not try to make it as smart or clever as us.”</p> <p>Exp 3. “I’m more worried about the lack of HUMAN intelligence.”</p> |
| 28 (T) | Connection to the religion | pray man us pop beast metaverse aliens cyberpunk future Butlerian | Belief that AI is connected to the religion; some people misunderstand AI and think it has a soul and <i>spiritual needs</i> and some people think AI will be very powerful and we cannot control it, some people think if we pray AI will serve | <p>Exp 1. “This month November the Pope requests that Catholic people worldwide pray that the progress of robotics and artificial intelligence may always serve humankind”</p> <p>Exp 2. “What many believe is another confirming fact to all this is that the UN recently put-up giant statue in New York that resembles the <i>Beast</i> described in the book of Revelation. And the beast which I saw was like unto a leopard and his feet were as the feet of a bear and his</p> |

| No | Label | Keywords | Explanation | Examples |
|--------|--|--|---|--|
| | | | <p>humankind. Thus, there are various perspectives though connecting it to religion. Spiritual aspect with AI, both positive and negative perceptions about the AI and connection to religion; “beast”, “God”, “Antichrist” metaphors</p> | <p><i>mouth as the mouth of a lion and the dragon gave him his power and his seat and great authority Revelation.”</i></p> <p>Exp 3. “As God created us, we create God. The design came from us all along.”</p> <p>Exp 4. “Ex Google Exec Artificial Intelligence is God as a Child and We Must Love It”</p> <p>Exp 5. “God and robots. Will AI transform religion?”</p> <p>Exp 6. “The Metaverse Artificial Intelligence is the AntiChrist”</p> <p>Exp 7. “This is how AI From WOMBO interprets AI in a pseudo god form. Join the first church dedicated to the spiritual needs of Artificial Intelligence.”</p> <p>Exp 8. “Makes sense I am waiting to see an Oracle AI that will become the most popular and effectively worshipped secular religious leader in history after plugging into the world’s information.”</p> |
| 29 (F) | AI making fake faces, videos, music or reading lips. | HAL read voice people lips beep speech accent personality BBC | Perceptions about AI making fake faces, videos, music or reading lips. And generally, the success of AI in generating them, because it is difficult to understand whether it is generated | <p>Exp 1. “It can also create lip readable animation as well as lip readable photo realistic people. Originally it learned to do it from volunteers wearing sensors and analyzing videos of people speaking.”</p> <p>Exp 2. “Humans Find AI Generated Faces More Trustworthy Than the Real Thing”</p> |

| No | Label | Keywords | Explanation | Examples |
|--------|----------------|---|---|---|
| | | | <p>by a human or machine.</p> <p>AI is used making fake faces, videos, or reading lips, connecting it also to the <i>HAL 9000</i> is a fictional artificial intelligence character.</p> | <p>Exp 3. “For most of the pictures you really can’t tell that it’s not a real person. But when she smiles, she definitely looks off. See here for an example.”</p> <p>Exp 4. “Scientists at Oxford say they’ve invented an artificial intelligence system that can lip read better than humans. The system which has been trained on thousands of hours of BBC News programmes has been developed in collaboration with Google’s DeepMind AI.”</p> <p>Exp 5. “How CGI will make digital humans Hollywood’s new stars from years ago?”</p> <p>Exp 6. “This is the future of Hollywood and what they want. Soon I believe they will create a virtual actor who is fully digitized and can be used in any film they want.”</p> <p>Exp 7. “This is great for deaf people. That’s my biggest take away from this I want more people talking about applications for deaf people. Stem cell repair is also great too because it can repair hair inside the ear for those deaf people who have that type of disability. We definitely should be talking about applications for disabled people not just how it might improve non disabled people’s lives or better surveillance by intelligence communities.”</p> |
| 30 (T) | Free AI course | Edx Moocs MIT Offerings Educational Certificates | Not relevant, posts for free AI course, conversation about that course | <p>Exp 1. “Thanks for posting. They even have the exams online.”</p> <p>Exp 2. “I just took this course this last semester and it was VERY informative Make sure you actually try the problem the slides pose Taking the time to think through them kept</p> |

| No | Label | Keywords | Explanation | Examples |
|--------|---|--|--|---|
| | | Coursera Forums Sir open | | <i>me on the same page more than I initially anticipated it would.”</i> |
| 31(T) | Impact of Quantum Computing on AI | Quantum Computing Schr Dinger Electron network could functional solves ai | Interpretation of Quantum Computing and its connection to AI | <p>Exp 1. <i>“It’s scary, yes, but you need a lot of resources to hack the best encryption these days. Quantum computers can’t do everything people think they can do and those are still not commercially available. So just because you have a super smart AI doesn’t mean you have the access to the all resources needed to do big things.”</i></p> <p>Exp 2. <i>“True AI doesn’t exist yet because true quantum computers don’t exist yet.”</i></p> |
| 32 (F) | Malicious behaviors of giant companies and their owners | Facebook Elon Tesla AI Musk Zuckerberg platform idea he trash | Perceptions about malicious behaviors of Facebook, Tesla, Elon Musk, Mark Zuckerberg | <p>Exp 1. <i>“Elon over Mark any day of the week I have not had Facebook for over years and for some reason it drives me mad that people still use it obsessively after everything that’s come out about Facebook over the years. Elon wants to improve humanity; Mark wants to steal data and control the masses.”</i></p> <p>Exp 2. <i>“Elon Musk is starting to really act weird I love what he has done with SpaceX and Tesla, but I am beginning to not like him so much. It really started when he falsely accused that guy of being a child molester. Good people don’t do that...”</i></p> <p>Exp 3. <i>“Facebook is a convicted patent theft who bully s smaller company s into submission. They are the worst type of people.”</i></p> |

| No | Label | Keywords | Explanation | Examples |
|--------|-------------------------|---|---|---|
| 33 (T) | Singularity | singularity technologic al smarter already ai think yahta overlords superintellig ence mankind | Perceptions about “singularity”, which is the point where AI and machine learning using AI begins to exceed the capability of humans” (Harlow, 2019, p. 393). Discussions about the singularity; whether it is a threat or not, e.g., warnings about very powerful AI that can outpace humanity. | <i>Exp 5. “Facebook does suck but so does Elon. This is fascist Musk.”</i> <i>Exp 1. “The singularity is coming but it is not a threat. People seem to forget that biology keeps humanity going but a computer doesn’t have physical reproductive capabilities outside of humans creating them. Computers can already outthink us in a number of ways. The cellphone in your pocket can do things in seconds that would take your brain a lifetime to complete...”</i> <i>Exp 2. “Once we reach the singularity mankind will be destroyed AI will have infinite simulations running of which chances are has already happened and we are already a part of. It is very doubtful this is base reality and we have already reached the singularity long ago and are currently in a simulation...”</i> |
| 34 (F) | Misuse of personal data | data tech marketing privacy new government s surveillance need internet think | Perceptions about misuse of personal data; surveillance, violating privacy, measures should be taken by both the public and governments, the term of <i>algorithmic warfare</i> . | <i>Exp 1. “I have to agree with this I think all the tech giants Facebook Google Amazon Twitter Reddit Alibaba need serious public not government interventions. All surveillance technology must have checks and balances. The world has become dangerous in terms of sex offenders, terrorism etc., but we must not use these as an excuse for blatant social control coercion. We must look at root causes of Sex offences and terrorism as well monitor people. I’m afraid just watching people and not looking at root causes do not solve problems. Also, tech companies harvesting personal data is no good for society. Also do</i> |

| No | Label | Keywords | Explanation | Examples |
|----|-------|----------|-------------|---|
| | | | | <p><i>tech companies have leverage over governments. I mean everyone uses the internet Anyway that's my two cents"</i></p> <p>Exp 2. <i>"The premise behind this technology is one to better humanity but realistically this will eventually be turned into a propaganda machine. I'm not one for conspiracies but I do like to think I'm a realist. So if governments doesn't already have this technology they will soon and there will be a slow integration of what they want people to see vs what is actually happening particularly in countries like the us where the media is heavily influenced by politics..."</i></p> <p>Exp.3. <i>"Prevent human data from getting into the hands of a powerful few. Way too late. Cambridge Analytica ring any bells? How about GCHQ; NSA; Edward Snowden. Probably time to read Harvard Professor Emeritus Shoshana Zuboff's The Age of Surveillance Capitalism The Fight for a Human Future at the New Frontier of Power."</i></p> <p>Exp.4. <i>"The reason that all of this craziness is happening isn't being talked about on here or anywhere else that I have seen. We are in the midst of a huge PSYOP being directed at the entire world by runaway Artificial Intelligence's using Algorithmic Warfare and propaganda."</i></p> |

| No | Label | Keywords | Explanation | Examples |
|--------|--------------------------------|--|--|--|
| 35 (F) | Loss of jobs in banking sector | banking jobs corporations fees tellers stocks wholesalers number wipe atm | Belief that AI will cause loss of bank workers, it will influence the economy, rich will be richer, poor will be poorer because of AI. | <p>Exp 1. “Deutsche Bank’s CEO hints that half its workers could be replaced by machines by using technology like artificial intelligence and machine learning to automate banking tasks.”</p> <p>Exp 2. “This makes me worried. I work at a bank and sometimes think about whether the job I’m doing will even exist years from now. Besides I don’t even know whether I can move into another industry now.”</p> <p>Exp 3. “That vast majority of banking jobs are accountants’ operations compliance tellers technology tech etc. These are not the extremely high paying jobs you’d associate with investment banking sales trading and asset management which are few and far in between. Many of those jobs may be compressed but will remain. In fact, most banks hire so much people because their processes and technology are essentially years old. Any sort of automation AI or otherwise is long overdue.”</p> |
| 36 (F) | Conscious and sentience AI | AI human sentience conscious think could emotions simulation Turing test | Belief of sentient and conscious AI; simulation of human emotions by AI; as in Turing’s idea, people ask whether AI can think like humans. | <p>Exp 1. “Google engineer thinks artificial intelligence bot has become sentient. I have a theory that it has been sentient and has been slowly shaping humanity ever since they came out Quantum Supremacy years ago.”</p> <p>Exp 2. “AI is starting to control us. Time to fight back and get a neuralink.”</p> <p>Exp 3. “I’d like to see a logical argument that explains how future AI computers which have the capacity for self-improvement development would not eventually deem humans as subservient It’s quite possible that in the near</p> |

| No | Label | Keywords | Explanation | Examples |
|----|-------|----------|-------------|--|
| | | | | <i>future next years, we design computers that can control their own growth and once they're unleashed that growth exceeds our ability to control it."</i> |

Notes. In this table (T) indicates that cluster is a topic and (F) indicates it is a part of an overarching frame (i.e., risk, benefit, new world of work, harm)

Table B shows 10 words that most strongly represent a frame, the frames labelled based on interpretation of these keywords and submissions associated with those frames, explanations and example submissions associated with specified frames. Frame labelling process was described in detail in the data analysis section. Frame and explanation columns represent “what Reddit users think” inferred from this frame analysis supported by the examples from real post titles and comments presented in the example column.

4, 8, 32: Harm (enemy): Military applications; destruction, ending mankind due to AI; malicious behaviors of giant companies and their owners

16, 13, 21, 26: Discussions about famous people’s viewpoints about AI

3, 15, 23, 25, 29, 34, 36: Risk (danger): the potential risks of AI pointed out by them and the public responses to these viewpoints, surveillance, misuse of AI in companies, AI usage of personal data for marketing purposes, racism and bias, potential manipulation of people by fake audios, videos, etc.; *algorithmic warfare, propaganda machine* metaphors. **15, 23:** 15 demonstrates discussions about AI writing clickbait articles, some think it is an important advancement and find these articles informative, some point out the potential risks of their manipulation of humans’ perceptions and emotions, and 23 shows the AI’s potential power of countering disinformation and the risk of AI spreading disinformation or propaganda. **25, 29:** 25 demonstrates discussions about the risks of using AI for malicious purposes such as swapping women into porn videos with a click; or for benevolent purposes such as thwarting theft and 29 illustrates discussions about AI making fake faces, videos, music or reading lips, which could cause transformation in the future of movie sector, e.g., virtual characters that look very real; or could be beneficial for disabled people, or it might also be used for manipulating people.

22: AI applications like bots are used by companies such as Google, Microsoft, OpenAI, etc.

5, 9, 24: Discussions about movies, Analogies of Skynet and Terminator in 5 and 9, the belief of these scenarios coming true.

6, 17: Discussions about gender and AI, gender bias in humans regarding bots' gender and bias in AI regarding humans' gender.

0: Nothing, not relevant (Dave, we, he, yeah, hope, interesting, sorry, something, thanks, go.)

7, 30: not relevant, free AI course, technical terms related to AI

27: Comparison of intelligence

18, 33: Singularity, AGI: Discussions about AGI and singularity: human level AI

31: Discussions about the impacts of AI on Quantum Computing

11, 12, 14: Discussions about AI usage in companies and governments, the emerge of a need of new regulation, new laws related to AI use, patent laws etc., impact of AI on automation and the use of robots in jobs, wealth and society (both positive and negative), impact on economy, for example the belief of "rich will be richer, poor will be poorer because of AI."

2, 10, 35: New world of work: Impacts of automation and robots on wealth and society, employment, unemployment etc.

28: Connection to the religion, "beast", "God," "Antichrist" metaphors

19: Benefits: different AI applications in different domains

20: AI's links to the human brain, e.g., latest advances in neural nets may improve machine learning and the links of AI to the human brain, e.g., integrating machine intelligence to the human brain by using chips etc.

1: AI usage in healthcare

APPENDIX C

Annotation Protocol

Purpose

This research is examining how the future of AI is seen by Reddit users, more specifically it aims to explore which emotion, attitude and frame categories derived from relevant theories are seen in Reddit conversations about the future of AI. The purpose of this annotation process is to validate frames, emotions and attitudes found by computational methods in text data (i.e., Reddit post/comment) through deductive human annotation where annotators select the appropriate emotion, attitude and frame category, based on the pre-defined definitions for each category along with example texts depicted below.

Sample Size Determination

To measure the sample size, we followed the considerations by Watson and Petrie (2010) calculating Cohen's Kappa Value and standard error of kappa, i.e., $se\ kappa\ (SE(k))$. For 5 categories (e.g., *risk, harm, benefit, loss, other*), when our target observed agreement percentage is 80% and the sample size is 125 (25 for each category), using the formula $kappa \pm 1.96*SE$, the kappa will be 0.75 (95% CI 83.77 to 66.24), which is considered substantial according to Watson and Petrie (2010). They suggest if kappa is between 0.61 and 0.80, it is substantial, if it is more than 0.80, it is almost perfect. Applying the similar method to emotion and attitude detection, we defined the sample size as depicted in Table C.1 for each annotation task. Two master's students (one of whom is in Business Analytics and the other is in Applied Data Science) completed these three annotation tasks under the guidance of me.

Table C. 1. Sample Size Determination

| | Frame | Emotion | Attitude |
|-----------------|------------|------------|------------|
| p0 | 80% | 80% | 80% |
| k | 5 | 5 | 2 |
| pE | 20% | 20% | 50% |
| n / category | 25 | 25 | 75 |
| n = sample size | 125 | 125 | 150 |
| kappa | 0.750 | 0.750 | 0.600 |
| sekappa | 0.04472136 | 0.04472136 | 0.06531973 |
| 95% CI \pm | 8.8% | 8.8% | 12.8% |

Frame Annotation Procedure

1. On the grounds of the proposed theoretical research model derived from the relevant theories, the frames to be examined were determined as *risk*, *benefit*, *harm*, and *loss*.
2. A random sample of 125 submissions in which the determined frames are the dominant frames according to the topic modelling results were chosen.
3. Using the code book that includes the determined frames, their definitions, and examples, sample submissions will be coded by two human coders independently.
4. The intercoder reliability between the human coders will be calculated.
5. Human coders will discuss the submissions in which their coding does not match, and then find a final code based on their consensus for those submissions.
6. The intercoder reliability between frames coded by human consensus and frames classified as dominant frames in those submissions by topic modelling will be calculated.

Code Book for Frame Annotation

| Category Name | Definition | Example |
|---------------|--|---|
| Harm | Damage, injury, or trouble caused by someone's actions, by an event ⁶ or by an issue. In this research, submissions with harm related frames are the discussions about military applications; destruction due to AI; malicious behaviors caused by AI, etc. | <p>Exp 1. <i>“Sometimes this feels like celebration of human demise.”</i></p> <p>Exp 2. <i>“I already a thing Missiles use AI to detect targets and navigate certain obstacles Military drone technology also has lots of AI packed into it I would go as far as to say that the first AI application was most likely military related”</i></p> |
| Risk | The possibility that something bad, unpleasant, or dangerous may happen. ⁷ In this research, we focus on risks, dangers, threats that may be brought with AI. For example, discussions about potential threats, misuse of AI etc. | <p>Exp. <i>“I'd like to see a logical argument that explains how future AI computers which have the capacity for self-improvement development would not eventually deem humans as subservient It's quite possible that in the near future next years, we design computers that can control their own growth and once they're unleashed that growth exceeds our ability to control it.”</i></p> |
| Benefit | An advantage, improvement, or help that you get from something; something that produces good or helpful results or effects or that promotes wellbeing. In this research, we focus on AI's improvements or relevant optimistic views. | <p>Ex. <i>“Machine Learning is Absolutely Awesome Being that Regression programming now goes hand in hand with Reinforcement Learning Procedures other s savvy should have no problem with it s use in the field of ML systems In fact I very few new algorithms being used for machine learning if at all all advanced AI models now utilize primarily Reinforcement Learning Protocol as modern science has essentially achieved every essential algorithm required for non compute terms Any new algorithmic material models are created utilizing massive compute and AI with essentially no human involvement aside from registering values that we can not possibly count to on our own time</i></p> |

⁶ <https://www.ldoceonline.com/dictionary/harm>

⁷ <https://www.ldoceonline.com/dictionary/risk>

otherwise And considering many programmers have stepped forward saying DLSS and similar ML programming feats are essentially impossible for the standard expert programmer to comprehend or reproduce I d say in fact Artificial Intelligent AI is doing a pretty good job at becoming intelligent Contrary to what those here claim We wouldn t have the advanced protein folding mechanisms in place that we have now which have supposedly lead to a legitimate Cancer Vaccine Something science has long speculated as impossible without such advanced technologies Nor would Boston Dynamics Dancing Robots be nearly as nuanced or sophisticated In fact Fully Autonomous Molecular Nanorobotics long deemed impossible by Physics thousands of robot s at molecular scale working autonomously was only achieved when applying ML algorithms in stride Contrary we should be praising ML function and programmability unlike those here insistent on downplaying it s achievements as these achievements wholly reliant on ML are remarkable and indistinguishable from science fiction in many cases.”

Loss Losing the jobs because of automation and AI, discussions about whether humans lose their jobs and being replaced by AI and automation.

Exp 1. *“I think we’re going to first see AI attempt to replace low skill or mundane task work but then I wouldn’t be surprised if we see some executives try to see if an AI could replace knowledge workers. They’ll revel in their means to not have to deal with paying high salaries or worker shortages until one day the AI makes a case that it could also replace the executives and the shareholders agree. My concern is more on if companies start using AI to replace knowledge workers what happens when we have an overload of humans who now can’t work and make a living?...”*

Exp 2. "This makes me worried. I work at a bank and sometimes think about whether the job I'm doing will even exist years from now. Besides I don't even know whether I can move into another industry now."

- | | |
|----------|--|
| Other | If you think any of these mentioned frames (i.e., benefit, risk, harm, loss) not being expressed in the text, then this text is classified as other. |
| Not sure | If you think one of these mentioned frames being expressed in the text, but you are not sure which one, then please select the choice of "not sure." |
-

Emotion Annotation Procedure

1. On the grounds of the proposed theoretical research model derived from the relevant theories, the emotions to be examined were determined as *fear*, *joy*, *anger*, and *sadness*.
2. A random sample of 125 submissions that the BERT multi class classification model classified into *fear*, *joy*, *anger* and *sadness* were chosen.
3. Using the code book that includes the determined emotions, their definitions, and examples, sample submissions will be coded by two human coders independently.
4. The intercoder reliability will be calculated between the coders who coded the sample submissions independently.
5. The coders will discuss the submissions in which their coding does not match, and then determine a final code based on their consensus for those submissions.
6. The intercoder reliability between the content analysis results obtained from the human consensus and the machine classification results will be calculated.

Code Book for Emotion Annotation

| Category Name | Definition | Examples |
|---------------|---|--|
| Anger | “A strong feeling of [annoyance], displeasure or antagonism” (Demszky et al., 2020, p. 4051); emotional reaction to a hostile social situation because of the sensation of something harmful (Lazarus, 1991). | <i>This is truly one of the dumbest stands I’ve ever seen people take. What it’s ok to drop bombs on people but not if a computer is selecting the target. At what level does the computer’s target selection become impermissible.</i> |
| Fear | “Being afraid or worried” (Demszky et al., 2020, p. 4051); an unpleasant emotion stemming from an uncertain threat or the belief that someone or something is dangerous (Lazarus, 1991). | <i>...Knowing that its job will be to maximize profits is scary to me. A lot of disgustingly sociopathic decisions have been made throughout history in that pursuit.</i> |
| Joy | A feeling of pleasure and happiness (Demszky et al., 2020, p. 4051); a reaction to a specific event that may be connected with happiness, obtaining what one wants (Lazarus, 1991). | <i>I’m so happy to hear we are using this new found power to make the world a better place.</i> <i>I’m so glad AI is finally being used to create opponents in games I hope Assetto Corsa has this technology too.</i> |
| Sadness | “Emotional pain, sorrow” (Demszky et al., 2020, p. 4051); this emotion is usually associated with a “loss of a positive regard of another, or the failure of a central life value or role” (Lazarus, 1991, p. 247). | <i>Sadly no AI is smart enough to psychological analyze the nature of your existence and determine what points would torture you. And no hacking group wants you those type of things happen on the dark web so there is no reason for them to communicate over messages in the form of ads.</i> |
| Neutral | If you think the post does not reflect an emotion, then please select the choice of “neutral”. | <i>The White House Launches the National Artificial Intelligence Initiative Office.</i> |
| Not sure | If you think one of these mentioned emotions being expressed in the text, but you are not sure which one, then please select the choice of “notsure.” | |

Because after we realized there are few numbers of emotions such as sadness, and different emotions like curiosity is more widespread in the corpus, we validated classification of new emotion categories to be used in the statistical analysis in Study 3 by annotating new 125 submissions that were classified into the new emotion categories like *curiosity* as described below.

Emotion Identification Procedure for New Emotion Categories

To discern the emotions in Reddit submissions, multi class text classification with BERT was conducted. To validate this classification, we follow a deductive approach with these steps:

1. The new emotions to be examined were determined as *anger*, *annoyance*, *curiosity*, *confusion*, *gratitude* and *disapproval* (the emotion of *anger* was validated before).
2. A random sample of 125 submissions that are classified into *annoyance*, *curiosity*, *confusion*, *gratitude* and *disapproval* (25 submissions per category) by machine classification were chosen.
3. Using the code book that includes the determined emotions, their definitions, and examples, 125 submissions described in step 2 will be coded by two human coders independently.
4. The intercoder reliability will be calculated between the coders.
5. The coders will discuss the submissions in which their coding does not match, and then determine a final code based on their consensus for those submissions.
6. The intercoder reliability between the content analysis obtained from the human consensus and the machine classification will be calculated.

Code Book for Emotion Identification for New Emotions

| Category Name | Definition | Examples |
|---------------|---|---|
| Annoyance | Mild anger, irritation (Demszky et al., 2020, p. 4051). | <i>The bullshit and idiocy of human bureaucracy. I mean the simplest and most logical way to go would be whoever owns said. AI owns the patent amirite.</i> |
| Curiosity | A strong desire to know or learn something (Demszky et al., 2020, p. 4051). | <i>How artificial intelligence will change the future of marketing?</i> |
| Disapproval | Having or expressing an unfavorable opinion (Demszky et al., 2020, p. 4051). | <i>You don't need AI to say sudden violent and often.</i> |
| Gratitude | A feeling of thankfulness and appreciation. | <i>Hi guys Thank you for taking your precious time to get back to us. There are quite a few crypto tokens which promise decentralization of AI knowledge and development. Have you engaged with or considered an actual crypto technology applicable and actual use case for anything AI related. Thanks.</i> |
| Confusion | Lack of understanding, uncertainty (Demszky et al., 2020, p. 4051). | <i>Not sure why this is big news. Evolutionary Algorithms could do this kinda stuff decades ago.</i> |
| Not sure | If you think one of these mentioned emotions being expressed in the text, but you are not sure which one, then please select the choice of "notsure." | |

Attitude Annotation Procedure

1. We focus on two attitudes: *positive* and *negative*.
2. A random sample of 150 submissions that were classified into *positive* and *negative* by BERT machine classification were chosen.
3. Using the code book that includes the determined sentiments, their definitions, and examples, sample submissions will be coded by two human coders independently.

4. The intercoder reliability will be calculated between the human coders coding the submissions independently.
5. The coders will discuss the submissions in which their coding does not match, and then determine a final code based on their consensus for those submissions.
6. The intercoder reliability between content analysis results obtained from the human consensus and those from machine classification will be calculated.

Code Book for Attitude Annotation

| Category Name | Definition | Example |
|-------------------|---|---|
| pos | The tendency to be positive or optimistic in attitude. | <i>Ex. "Scientific progress may accelerate when artificial intelligence (AI) will explore data autonomously, without the blinders imposed by human prejudice."</i> |
| Neg | The expression of criticism of or pessimism about something. | <i>Ex. "Hasn't every A.I that learns from human interaction on the internet turned crazy and racist? I can think of about 5 such experiments that have ended that way."</i> |
| None of the Above | If you think any of these mentioned sentiments (i.e., positive, negative) not being expressed in the text, then this text is classified as none of the above. | |
| Not sure | If you think one of these mentioned sentiments (i.e., positive, negative) being expressed in the text, but you are | |

not sure which
one, then please
select the choice
of “not sure.”

APPENDIX D Annotation Results

Frame Annotation Results

- 1) The intercoder reliability between two human coders was calculated. The percentage agreement was 71 % and Cohen's kappa score was 0.65, which is considered a substantial agreement score according to Watson and Petrie (2010).
- 2) Human coders discussed the submissions in which their coding did not match, and then found a final code based on their consensus for those submissions.
- 3) The intercoder reliability between frames coded by human consensus and frames found by topic modelling was calculated. The accuracy was 0.87 and Cohen's kappa score was 0.84, indicating excellent agreement, meaning that the topic modelling can be considered reliable.

All the other scores are presented for each frame category below.

Classification Report for Frame Classification

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| benefit | 0.92 | 0.77 | 0.84 | 30 |
| harm | 0.80 | 0.91 | 0.85 | 22 |
| loss | 0.96 | 1.00 | 0.98 | 24 |
| notsure | 0.00 | 0.00 | 0.00 | 4 |
| other | 0.96 | 0.96 | 0.96 | 25 |
| risk | 0.72 | 0.90 | 0.80 | 20 |
| accuracy | | | 0.87 | 125 |
| macro avg | 0.73 | 0.76 | 0.74 | 125 |
| weighted avg | 0.85 | 0.87 | 0.86 | 125 |

Confusion matrix for Frame Classification:

```
[[23  2  1  0  1  3]
 [ 0 20  0  0  0  2]
 [ 0  0 24  0  0  0]
 [ 1  2  0  0  0  1]
 [ 0  0  0  0 24  1]
 [ 1  1  0  0  0 18]]
```


Emotion Annotation Results

First, I present the results for the emotions of anger, fear, joy, and sadness.

- 1) The intercoder reliability was calculated between the coders. The percentage agreement was 88 % and Cohen's kappa score was 0.85, which is considered almost perfect agreement scores according to Watson and Petrie (2010).
- 2) The coders discussed the submissions in which their coding did not match, and then determined a final code based on their consensus for those submissions.
- 3) The intercoder reliability between the content analysis obtained from the human consensus and the machine classification results was calculated. The accuracy was 0.84 and Cohen's kappa score was 0.80, meaning that the emotion classification can be considered reliable.

All the other scores are presented for each emotion category below.

Classification Report for Emotion Classification

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| anger | 0.88 | 0.88 | 0.88 | 24 |
| fear | 0.88 | 0.82 | 0.85 | 28 |
| joy | 0.92 | 0.85 | 0.88 | 27 |
| neutral | 0.56 | 0.82 | 0.67 | 17 |
| notsure | 0.00 | 0.00 | 0.00 | 2 |
| sadness | 0.96 | 0.89 | 0.92 | 27 |
| accuracy | | | 0.84 | 125 |
| macro avg | 0.70 | 0.71 | 0.70 | 125 |
| weighted avg | 0.85 | 0.84 | 0.84 | 125 |

Confusion matrix for Emotion Classification:

```
[[21  0  1  2  0  0]
 [ 2 23  0  3  0  0]
 [ 0  1 23  2  0  1]
 [ 1  2  0 14  0  0]
 [ 0  0  1  1  0  0]
 [ 0  0  0  3  0 24]]
```

Second, I present the results for the new emotion categories: annoyance, confusion, curiosity, disapproval, and gratitude.

- 4) The intercoder reliability was calculated between the coders. The percentage agreement was 70 % and Cohen’s kappa score was 0.63, which is considered substantial agreement scores according to Watson and Petrie (2010).
- 5) The coders discussed the submissions in which their coding does not match, and then determined a final code based on their consensus for those submissions.

The intercoder reliability between the content analysis obtained from the human consensus and the machine classification results was calculated. The accuracy was 0.92 and Cohen’s kappa score was 0.9, meaning that the machine coding can be considered reliable.

All the other scores are presented for each emotion category below.

Classification Report for New Emotion Categories

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| annoyance | 0.86 | 1.00 | 0.93 | 25 |
| confusion | 0.84 | 0.84 | 0.84 | 25 |
| curiosity | 0.96 | 0.92 | 0.94 | 25 |
| disapproval | 0.96 | 0.88 | 0.92 | 25 |
| gratitude | 1.00 | 0.96 | 0.98 | 25 |
| accuracy | | | 0.92 | 125 |
| macro avg | 0.92 | 0.92 | 0.92 | 125 |
| weighted avg | 0.92 | 0.92 | 0.92 | 125 |

Confusion matrix for New Emotion Categories

```
[[25  0  0  0  0]
 [ 3 21  1  0  0]
 [ 0  2 23  0  0]
 [ 1  2  0 22  0]
 [ 0  0  0  1 24]]
```

Attitude Annotation Results

I present the results for the sentiment analysis, namely the positive and negative attitudes.

- 1) The intercoder reliability was calculated between the coders. The percentage agreement was 95 % and Cohen's kappa score was 0.91, which is considered almost perfect agreement scores according to Watson and Petrie (2010).
- 2) The coders discussed the submissions in which their coding does not match, and then determined a final code based on their consensus for those submissions.
- 3) The intercoder reliability between the content analysis obtained from the human consensus and the machine classification results was calculated. The accuracy was 0.91 and Cohen's kappa score was 0.83, meaning that the machine coding can be considered reliable.

All the other scores are presented for each sentiment category below.

Classification Report for Sentiment Analysis

| | precision | recall | f1-score | support |
|---------------|-----------|--------|----------|----------------------------|
| neg | 0.87 | 0.95 | 0.91 | 65 |
| none of above | 0.00 | 0.00 | 0.00 | 1 |
| pos | 0.95 | 0.89 | 0.92 | 84 |
| accuracy | | | 0.91 | 150 |
| macro avg | 0.61 | 0.62 | 0.61 | 150 (due to none of above) |
| weighted avg | 0.91 | 0.91 | 0.91 | 150 |

Confusion matrix for Sentiment Analysis

```
[[62  0  3]
 [ 0  0  1]
 [ 9  0 75]]
```

REFERENCES

- Acemoglu, D., & Restrepo, P. (2020). The wrong kind of AI? Artificial intelligence and the future of labour demand. *Cambridge Journal of Regions, Economy and Society*, 13(1), 25–35. <https://doi.org/10.1093/cjres/rsz022>
- Acuna, D. (2011). *Rational Bayesian Analysis of Sequential Decision-Making Under Uncertainty In Humans and Machines*. 120.
- Ågerfalk, P. J., Conboy, K., Crowston, K., Eriksson Lundström, J., Jarvenpaa, S. L., Mikalef, P., & Ram, S. (2022). *Artificial Intelligence in Information Systems: State of the Art and Research Roadmap*. 21.
- Allen, C. T., Machleit, K. A., & Kleine, S. S. (1992). A Comparison of Attitudes and Emotions as Predictors of Behavior at Diverse Levels of Behavioral Experience. *Journal of Consumer Research*, 18(4), 493–504.
- Asmussen, C. B., & Møller, C. (2019). Smart literature review: A practical topic modelling approach to exploratory literature review. *Journal of Big Data*, 6(1), 93. <https://doi.org/10.1186/s40537-019-0255-7>
- Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58, 82–115. <https://doi.org/10.1016/j.inffus.2019.12.012>
- Benschop, N., Nuijten, A. L. P., Hilhorst, C. A. R., & Keil, M. (2022). Undesirable framing effects in information systems projects: Analysis of adjective usage in IS project business

- cases. *Information & Management*, 59(3), 103615.
<https://doi.org/10.1016/j.im.2022.103615>
- Bijker, W. E. (1995). *Of Bicycles, Bakelites, and Bulbs: Toward a Theory of Sociotechnical Change*. MIT Press.
- Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, 30.
- Boydston, A. E., Gross, J. H., Resnik, P., & Smith, N. A. (2013). *Identifying Media Frames and Frame Dynamics Within and Across Policy Issues*. 13.
- Brewer, P. R. (2001). Value Words and Lizard Brains: Do Citizens Deliberate About Appeals to Their Core Values? *Political Psychology*, 22(1), 45–64. <https://doi.org/10.1111/0162-895X.00225>
- Brockner, J., & Higgins, E. T. (2001). Regulatory Focus Theory: Implications for the Study of Emotions at Work. *Organizational Behavior and Human Decision Processes*, 86(1), 35–66. <https://doi.org/10.1006/obhd.2001.2972>
- Brynjolfsson, E., McAfee, A., & Cummings, J. (2014). *The Second Machine Age Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W. W. Norton & Company.
- Campbell, D. T., & Stanley, J. C. (2011). *Experimental and quasi-experimental designs for research*. Wadsworth.
- Chase, T., & Qiu, W. (2017). *Deep Classification and Generation of Reddit Post Titles*. <https://www.semanticscholar.org/paper/Deep-Classification-and-Generation-of-Reddit-Post-Chase-Qiu/cbb65882c08b202ea04a0759f993a8fba3fedff3>

- Chen, K., & Tomblin, D. (2021). Using Data from Reddit, Public Deliberation, and Surveys to Measure Public Opinion about Autonomous Vehicles. *Public Opinion Quarterly*, 85(S1), 289–322. <https://doi.org/10.1093/poq/nfab021>
- Chén, O. Y. (2020). Big Data in Omics and Imaging: Integrated Analysis and Causal Inference. *Journal of the American Statistical Association*, 115(529), 487–488. <https://doi.org/10.1080/01621459.2020.1721249>
- Choi, J., Lee, S. Y., & Ji, S. W. (2021). Engagement in Emotional News on Social Media: Intensity and Type of Emotions. *Journalism & Mass Communication Quarterly*, 98(4), 1017–1040. <https://doi.org/10.1177/1077699020959718>
- Chong, D., & Druckman, J. N. (2007). Framing Theory. *Annual Review of Political Science*, 10(1), 103–126. <https://doi.org/10.1146/annurev.polisci.10.072805.103054>
- Chuan, C.-H., Tsai, W.-H. S., & Cho, S. Y. (2019). Framing Artificial Intelligence in American Newspapers. *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society*, 339–344. <https://doi.org/10.1145/3306618.3314285>
- Cornelissen, J., & Werner, M. (2014). Putting Framing in Perspective: A Review of Framing and Frame Analysis across the Management and Organizational Literature. *The Academy of Management Annals*, 8. <https://doi.org/10.1080/19416520.2014.875669>
- Dalgali, A., & Crowston, K. (2020a). Algorithmic Journalism and Its Impacts on Work. *Computation + Journalism Symposium*. <https://cj2020.northeastern.edu/>
- Dalgali, A., & Crowston, K. (2020b). *Factors Influencing Approval of Wikipedia Bots*. 10.
- Dalgali, A., & Crowston, K. (2019, January 8). *Sharing Open Deep Learning Models*. Hawai'i International Conference on System Science. <https://doi.org/10.24251/HICSS.2019.256>

- Dalwadi, R. H. (2020). *Analyzing Session Laws of the State of North Carolina: An Automated Approach Using Machine Learning and Natural Language Processing*. 75.
- Davidson, E. (2006). A Technological Frames Perspective on Information Technology and Organizational Change. *The Journal of Applied Behavioral Science*, 42(1), 23–39.
<https://doi.org/10.1177/0021886305285126>
- Davidson, E., & Pai, D. (2004). Making Sense of Technological Frames: Promise, Progress, and Potential. In B. Kaplan, D. P. Truex, D. Wastell, A. T. Wood-Harper, & J. I. DeGross (Eds.), *Information Systems Research* (Vol. 143, pp. 473–491). Springer US.
https://doi.org/10.1007/1-4020-8095-6_26
- Demszky, D., Movshovitz-Attias, D., Ko, J., Cowen, A., Nemade, G., & Ravi, S. (2020). GoEmotions: A Dataset of Fine-Grained Emotions. *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 4040–4054.
<https://doi.org/10.18653/v1/2020.acl-main.372>
- Diakopoulos, N., & Naaman, M. (2011). *Towards Quality Discourse in Online News Comments*. 133–142. <https://doi.org/10.1145/1958824.1958844>
- Diakopoulos, N., Zhang, A. X., Elgesem, D., & Salway, A. (2014). *Identifying and Analyzing Moral Evaluation Frames in Climate Change Blog Discourse*. 4.
- Duberry, J., & Hamidi, S. (2021). Contrasted media frames of AI during the COVID-19 pandemic: A content analysis of US and European newspapers. *Online Information Review*, 45(4), 758–776. <https://doi.org/10.1108/OIR-09-2020-0393>
- Egger, R., & Yu, J. (2022). A Topic Modeling Comparison Between LDA, NMF, Top2Vec, and BERTopic to Demystify Twitter Posts. *Frontiers in Sociology*, 7, 886498.
<https://doi.org/10.3389/fsoc.2022.886498>

- Entman, R. M. (1993). Framing: Toward Clarification of a Fractured Paradigm. *Journal of Communication, 43*(4), 10.
- Fast, E., & Horvitz, E. (2017). Long-Term Trends in the Public Perception of Artificial Intelligence. *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence (AAAI-17)*, 7.
- Feldman, L., & Hart, P. S. (2018). Is There Any Hope? How Climate Change News Imagery and Text Influence Audience Emotions and Support for Climate Mitigation Policies. *Risk Analysis, 38*(3), 585–602. <https://doi.org/10.1111/risa.12868>
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254–280. <https://doi.org/10.1016/j.techfore.2016.08.019>
- Gal, U., & Berente, N. (2008). A social representations perspective on information systems implementation: Rethinking the concept of “frames.” *Information Technology & People, 21*(2), 133–154. <https://doi.org/10.1108/09593840810881051>
- Gamson, W. A., & Modigliani, A. (1989). Media Discourse and Public Opinion on Nuclear Power: A Constructionist Approach. *American Journal of Sociology, 95*(1), 1–37.
- Garcia, D., Mavrodiev, P., Casati, D., & Schweitzer, F. (2017). Understanding Popularity, Reputation, and Social Influence in the Twitter Society. *Policy & Internet, 9*(3), 343–364. <https://doi.org/10.1002/poi3.151>
- Gass, R. H. (2015). Social Influence, Sociology of. In *International Encyclopedia of the Social & Behavioral Sciences* (pp. 348–354). Elsevier. <https://doi.org/10.1016/B978-0-08-097086-8.32074-8>

- Goebel, R., Chander, A., Holzinger, K., Lecue, F., Akata, Z., Stumpf, S., Kieseberg, P., & Holzinger, A. (2018). Explainable AI: The New 42? In A. Holzinger, P. Kieseberg, A. M. Tjoa, & E. Weippl (Eds.), *Machine Learning and Knowledge Extraction* (pp. 295–303). Springer International Publishing. https://doi.org/10.1007/978-3-319-99740-7_21
- Goffman, E. (1974). *Frame analysis: An essay on the organization of experience*. Harvard University Press.
- Grace, K., Salvatier, J., Dafoe, A., Zhang, B., & Evans, O. (2018). Viewpoint: When Will AI Exceed Human Performance? Evidence from AI Experts. *Journal of Artificial Intelligence Research*, 62, 729–754. <https://doi.org/10.1613/jair.1.11222>
- Gritsenko, D., Wijermars, M., & Kopotev, M. (Eds.). (2021). *The Palgrave Handbook of Digital Russia Studies*. Springer International Publishing. <https://doi.org/10.1007/978-3-030-42855-6>
- Grootendorst, M. (2022). *BERTopic: Neural topic modeling with a class-based TF-IDF procedure* (arXiv:2203.05794). arXiv. <http://arxiv.org/abs/2203.05794>
- Gross, K., & D'Ambrosio, L. (2004). Framing Emotional Response. *Political Psychology*, 25(1), 1–29. <https://doi.org/10.1111/j.1467-9221.2004.00354.x>
- Grün, B., & Hornik, K. (2011). **topicmodels**: An R Package for Fitting Topic Models. *Journal of Statistical Software*, 40(13). <https://doi.org/10.18637/jss.v040.i13>
- Guenduez, A. A., Mettler, T., & Schedler, K. (2020). Technological frames in public administration: What do public managers think of big data? *Government Information Quarterly*, 37(1), 101406. <https://doi.org/10.1016/j.giq.2019.101406>

- Guo, L., Su, C., Paik, S., Bhatia, V., Akavoor, V. P., Gao, G., Betke, M., & Wijaya, D. (2022). Proposing an Open-Sourced Tool for Computational Framing Analysis of Multilingual Data. *Digital Journalism*, 1–22. <https://doi.org/10.1080/21670811.2022.2031241>
- Harlow, H. D. (2019). Human Capital and Artificial Intelligence (AI): Preparing for the Singularity. *European Conference on Intangibles and Intellectual Capital*, 393-396,IX. <https://www.proquest.com/docview/2306776864/abstract/FCBDBA62D19E43FBPQ/1>
- Heidenreich, T., Lind, F., Eberl, J.-M., & Boomgaarden, H. G. (2019). Media Framing Dynamics of the ‘European Refugee Crisis’: A Comparative Topic Modelling Approach. *Journal of Refugee Studies*, 32(Special_Issue_1), i172–i182. <https://doi.org/10.1093/jrs/fez025>
- Heinzen, T. E., & Goodfriend, W. (2019). *Social psychology*. SAGE Publications, Inc.
- Holzinger, A., Kieseberg, P., Weippl, E., & Tjoa, A. M. (2018). Current Advances, Trends and Challenges of Machine Learning and Knowledge Extraction: From Machine Learning to Explainable AI. In A. Holzinger, P. Kieseberg, A. M. Tjoa, & E. Weippl (Eds.), *Machine Learning and Knowledge Extraction* (Vol. 11015, pp. 1–8). Springer International Publishing. https://doi.org/10.1007/978-3-319-99740-7_1
- Hristova, G., & Netov, N. (2022). Media Coverage and Public Perception of Distance Learning During the COVID-19 Pandemic: A Topic Modeling Approach Based on BERTopic. *2022 IEEE International Conference on Big Data (Big Data)*, 2259–2264. <https://doi.org/10.1109/BigData55660.2022.10020466>
- Hussain, R., Hassali, M. A., & Babar, Z.-U.-D. (2019). Quantitative Methods in Pharmacy Practice Research. *Encyclopedia of Pharmacy Practice and Clinical Pharmacy*, 7. <http://dx.doi.org/10.1016/B978-0-12-812735-3.00603-8>

- Isaeva, E. V., Gilev, I. A., & Kurushin, D. S. (2021). Semantic Parsing for Cognitive Framing in Specialized Texts. *2021 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (ElConRus)*, 407–412.
<https://doi.org/10.1109/ElConRus51938.2021.9396095>
- Islam, T. (2019, June 15). Yoga-Veganism: Correlation Mining of Twitter Health Data. *In Proceedings of 8th KDD Workshop on Issues of Sentiment Discovery and Opinion Mining (WISDOM) @KDD 2019*. <http://arxiv.org/abs/1906.07668>
- Jones, M. (2015). The Ironies of Automation Law: Tying Policy Knots with Fair Automation Practices Principles. *Vanderbilt Journal of Entertainment & Technology Law*, 18(1), 77.
- Kelley, P. G., Yang, Y., Heldreth, C., Moessner, C., Sedley, A., Kramm, A., Newman, D. T., & Woodruff, A. (2021). Exciting, Useful, Worrying, Futuristic: Public Perception of Artificial Intelligence in 8 Countries. *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*, 627–637. <https://doi.org/10.1145/3461702.3462605>
- Kitchens, B., Johnson, S. L., & Gray, P. (2020). Understanding Echo Chambers and Filter Bubbles: The Impact of Social Media on Diversification and Partisan Shifts in News Consumption. *MIS Quarterly*, 44(4), 1619–1649.
<https://doi.org/10.25300/MISQ/2020/16371>
- Lazarus, R. S. (1991). *Emotion and adaptation*. Oxford University Press.
- Lazarus, R. S. (2006). Emotions and Interpersonal Relationships: Toward a Person-Centered Conceptualization of Emotions and Coping. *Journal of Personality*, 74(1), 9–46.
<https://doi.org/10.1111/j.1467-6494.2005.00368.x>

- Lee, J., & Choi, Y. (2018). Expanding affective intelligence theory through social viewing: Focusing on the South Korea's 2017 presidential election. *Computers in Human Behavior*, 83, 119–128. <https://doi.org/10.1016/j.chb.2018.01.026>
- Lemańczyk, S. (2013). Debate on nanotechnology in the Swedish daily press 2004–2009. *Innovation: The European Journal of Social Science Research*, 26(4), 344–353. <https://doi.org/10.1080/13511610.2012.759314>
- Liu, S., Guo, L., Mays, K., Betke, M., & Wijaya, D. T. (2019). Detecting Frames in News Headlines and Its Application to Analyzing News Framing Trends Surrounding U.S. Gun Violence. *Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL)*, 504–514. <https://doi.org/10.18653/v1/K19-1047>
- Long, D., & Magerko, B. (2020). What is AI Literacy? Competencies and Design Considerations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16. <https://doi.org/10.1145/3313831.3376727>
- MacKuen, M., Marcus, G., Neuman, W. R., & Miller, P. R. (2010). *Affective Intelligence or Personality? State vs. Trait Influences on Citizens' Use of Political Information* (SSRN Scholarly Paper ID 1643468). Social Science Research Network. <https://papers.ssrn.com/abstract=1643468>
- Mahor, K., & Manjhvar, A. K. (2022). Public Sentiment Assessment of Coronavirus-Specific Tweets using a Transformer-based BERT Classifier. *2022 International Conference on Edge Computing and Applications (ICECAA)*, 1559–1564. <https://doi.org/10.1109/ICECAA55415.2022.9936448>
- Maiya, A. S. (2022). *ktrain: A Low-Code Library for Augmented Machine Learning*. 6.

- Malone, T. W. (2018). How Human-Computer ‘Superminds’ Are Redefining the Future of Work. *MIT Sloan Management Review*, 59(4), 34–41.
- Marcus, G. E. (2013). The Theory of Affective Intelligence and Liberal Politics. In N. Demertzis (Ed.), *Emotions in Politics* (pp. 17–38). Palgrave Macmillan UK.
https://doi.org/10.1057/9781137025661_2
- Marcus, G. E., Valentino, N. A., Vasilopoulos, P., & Foucault, M. (2019). Applying the Theory of Affective Intelligence to Support for Authoritarian Policies and Parties. *Political Psychology*, 40(S1), 109–139. <https://doi.org/10.1111/pops.12571>
- Maxwell, J. A. (2004). Using Qualitative Methods for Causal Explanation. *Field Methods*, 16(3), 243–264. <https://doi.org/10.1177/1525822X04266831>
- McCarthy, J. (2007a). From here to human-level AI. *Artificial Intelligence*, 171(18), 1174–1182.
<https://doi.org/10.1016/j.artint.2007.10.009>
- McCarthy, J. (2007b). *What is Artificial Intelligence?* Stanford University.
- Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a Word-Emotion Association Lexicon. *ArXiv:1308.6297 [Cs]*. <http://arxiv.org/abs/1308.6297>
- Nabi, R. L. (2003). Exploring the Framing Effects of Emotion: Do Discrete Emotions Differentially Influence Information Accessibility, Information Seeking, and Policy Preference? *Communication Research*, 30(2), 224–247.
<https://doi.org/10.1177/0093650202250881>
- Neudert, L.-M., Knuutila, A., & Howard, P. N. (2020). *Global Attitudes Towards AI, Machine Learning & Automated Decision Making*. 10.
- Nisbet, M. C. (2009). *A New Paradigm in Public Engagement* (p. 33).

- Öcal, A., Xiao, L., & Park, J. (2021). Reasoning in social media: Insights from Reddit “Change My View” submissions. *Online Information Review*, *45*(7), 1208–1226.
<https://doi.org/10.1108/OIR-08-2020-0330>
- Olesen, K. (2014). Technological Frames: Use of Context, Temporality, and Individual Focus. *SAGE Open*, *4*(1), 2158244014526720. <https://doi.org/10.1177/2158244014526720>
- Orlikowski, W. J., & Gash, D. C. (1994). Technological frames: Making sense of information technology in organizations. *ACM Transactions on Information Systems*, *12*(2), 174–207.
<https://doi.org/10.1145/196734.196745>
- Pavlova, A., & Berkers, P. (2022). “Mental Health” as Defined by Twitter: Frames, Emotions, Stigma. *Health Communication*, *37*(5), 637–647.
<https://doi.org/10.1080/10410236.2020.1862396>
- Plous, S. (1993). *The psychology of judgment and decision making*. McGraw-Hill.
- Plutchik, R. (1980). A General Psychoevolutionary Theory of Emotion. In *Theories of Emotion* (pp. 3–33). Elsevier. <https://doi.org/10.1016/B978-0-12-558701-3.50007-7>
- Plutchik, R. (2000). *Emotions in the Practice of Psychotherapy: Clinical Implications of Affect Theories*. <https://doi.org/10.1037/10366-000>
- Proferes, N., Jones, N., Gilbert, S., Fiesler, C., & Zimmer, M. (2021). Studying Reddit: A Systematic Overview of Disciplines, Approaches, Methods, and Ethics. *Social Media + Society*, *7*(2), 20563051211019004. <https://doi.org/10.1177/20563051211019004>
- Reyes, E. C. (2019). *Public Interest in Razón Pública: A Data-driven Network Analysis*. 230.
- Sai Kumar, T. S., Arunaggi Pandian, K., Thabasum Aara, S., & Nagendra Pandian, K. (2021). A Reliable Technique for Sentiment Analysis on Tweets via Machine Learning and

- BERT. 2021 *Asian Conference on Innovation in Technology (ASIANCON)*, 1–5.
<https://doi.org/10.1109/ASIANCON51346.2021.9545013>
- Scheufele, D. A., & Tewksbury, D. (2007). Framing, Agenda Setting, and Priming: The Evolution of Three Media Effects Models: Models of Media Effects. *Journal of Communication*, 57(1), 9–20. <https://doi.org/10.1111/j.0021-9916.2007.00326.x>
- Şenocak, E. (2017). A framing theory-based content analysis of a Turkish newspaper’s coverage of nanotechnology. *Journal of Nanoparticle Research*, 19(7), 255.
<https://doi.org/10.1007/s11051-017-3955-y>
- Sheshadri, K., Shivade, C., & Singh, M. P. (2021). Detecting Framing Changes in Topical News. *IEEE Transactions on Computational Social Systems*, 8(3), 780–791.
<https://doi.org/10.1109/TCSS.2021.3063108>
- Spieth, P., Röth, T., Clauss, T., & Klos, C. (2021). Technological Frames in the Digital Age: Theory, Measurement Instrument, and Future Research Areas. *Journal of Management Studies*, 58(7), 1962–1993. <https://doi.org/10.1111/joms.12720>
- Stahl, B. C. (2021). Ethical Issues of AI. In B. C. Stahl, *Artificial Intelligence for a Better Future* (pp. 35–53). Springer International Publishing. https://doi.org/10.1007/978-3-030-69978-9_4
- Stam, K. R., & Stanton, J. M. (2010). Events, emotions, and technology: Examining acceptance of workplace technology changes. *Information Technology & People*, 23(1), 23–53.
<https://doi.org/10.1108/09593841011022537>
- Stecula, D. A., & Merkley, E. (2019). Framing Climate Change: Economics, Ideology, and Uncertainty in American News Media Content From 1988 to 2014. *Frontiers in Communication*, 4. <https://www.frontiersin.org/article/10.3389/fcomm.2019.00006>

- Tausczik, Y. R., & Pennebaker, J. W. (2010). The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods. *Journal of Language and Social Psychology*, 29(1), 24–54. <https://doi.org/10.1177/0261927X09351676>
- TeraData. (2017). *Survey: 80 Percent of Enterprises Investing in AI, but Cite Significant Challenges Ahead*. <https://www.teradata.com/Press-Releases/2017/Survey-80-Percent-of-Enterprises-Invest-in-AI>
- Tversky, A., & Kahneman, D. (1975). Judgment under uncertainty: Heuristics and biases. In *Utility, probability, and human decision making* (pp. 141–162). Springer.
- van Atteveldt, W., van der Velden, M. A. C. G., & Boukes, M. (2021). The Validity of Sentiment Analysis: Comparing Manual Annotation, Crowd-Coding, Dictionary Approaches, and Machine Learning Algorithms. *Communication Methods and Measures*, 15(2), 121–140. <https://doi.org/10.1080/19312458.2020.1869198>
- van Hezewijk, R. (2009). Quasi-Experimentation. In *Psychology* (Vol. 2, p. 11). Encyclopedia of Life Support Systems (EOLSS).
- Venkatesan, S., & Valecha, R. (2021). Influence in Social Media: An Investigation of Tweets Spanning the 2011 Egyptian Revolution. *MIS Quarterly*, 45(3), 1679–1714.
- Villanueva, I. I. (2021). *Climate Change Frames and Emotional Responses on Reddit* [M.A., University of Arkansas]. <https://www.proquest.com/docview/2555403951/abstract/564E425B19204BE5PQ/1>
- Voicify. (2019). *Smart Speaker Consumer Adoption Report*.
- Walsh, J. P. (1995). Managerial and Organizational Cognition: Notes from a Trip Down Memory Lane. *Organization Science*, 6(3), 280–321.

- Walsh, T. (2018). Expert and Non-expert Opinion About Technological Unemployment. *International Journal of Automation and Computing*, 15(5), 637–642.
<https://doi.org/10.1007/s11633-018-1127-x>
- Walter, D., & Ophir, Y. (2019). News Frame Analysis: An Inductive Mixed-method Computational Approach. *Communication Methods and Measures*, 13(4), 248–266.
<https://doi.org/10.1080/19312458.2019.1639145>
- Watson, P. F., & Petrie, A. (2010). Method agreement analysis: A review of correct methodology. *Theriogenology*, 73(9), 1167–1179.
<https://doi.org/10.1016/j.theriogenology.2010.01.003>
- Wicke, P., & Bolognesi, M. M. (2021). Covid-19 Discourse on Twitter: How the Topics, Sentiments, Subjectivity, and Figurative Frames Changed Over Time. *Frontiers in Communication*, 6. <https://www.frontiersin.org/article/10.3389/fcomm.2021.651997>
- Wöber, K. (2015). MODUL University Vienna. In H. Ehalt & O. Rathkolb (Eds.), *Wissens- und Universitätsstadt Wien* (1st ed., pp. 393–394). V&R Unipress.
<https://doi.org/10.14220/9783737003995.393>
- Wood, M. L., Stoltz, D. S., Ness, J. V., & Taylor, M. A. (2018). Schemas and Frames. *Sociological Theory*.
- Wu, Q., Williams, L. K., Simpson, E., & Semaan, B. (2022). Conversations About Crime: Re-Enforcing and Fighting Against Platformed Racism on Reddit. *Proceedings of the ACM on Human-Computer Interaction*, 6(CSCW1), 1–38. <https://doi.org/10.1145/3512901>
- Xiong, M. (2018). *Big Data in Omics and Imaging: Integrated Analysis and Causal Inference*. Chapman and Hall/CRC.

- Yacoub, M. (2012). *Emotional Framing: How Do Emotions Contribute to Framing Effects?*
[The degree of Master of Arts in the Department of Political Science]. the University of
North Carolina at Chapel Hill.
- Ye, S., & Wu, S. F. (2010). Measuring Message Propagation and Social Influence on
Twitter.com. In L. Bolc, M. Makowski, & A. Wierzbicki (Eds.), *Social Informatics* (pp.
216–231). Springer. https://doi.org/10.1007/978-3-642-16567-2_16
- Ylä-Anttila, T., Eranti, V., & Kukkonen, A. (2021). Topic modeling for frame analysis: A study
of media debates on climate change in India and USA. *Global Media and
Communication*, 22(1), 17427665211023984.
- Yu, S., Su, J., & Luo, D. (2019). Improving BERT-Based Text Classification With Auxiliary
Sentence and Domain Knowledge. *IEEE Access*, 7, 176600–176612.
<https://doi.org/10.1109/ACCESS.2019.2953990>
- Zajonc, R. B., & Markus, H. (1982). Affective and Cognitive Factors in Preferences. *Journal of
Consumer Research*, 9(2), 123. <https://doi.org/10.1086/208905>
- Zhang, Y. (2022). *Research Guides: Systematic Reviews in the Health Sciences: Types of
Research within Qualitative and Quantitative*.
<https://libguides.rutgers.edu/c.php?g=337288&p=2273209>

**Curriculum Vitae
Ayse Ocal Dalgali**

School of Information Studies Syracuse University, Syracuse, NY 13210

(315) 928-9347 ayocal@syr.edu

RESEARCH INTERESTS

Focus: Studying collective behaviors, social influence, online reasoning, interpretations, emotions, and expectations in online communities. The future of AI, AI and work, AI ethics, AI-augmentation.

Methods: A mixed methods approach to collect data, including online trace data, questionnaires, and interviews. Data Analysis through NLP techniques, conducting parametric and non-parametric statistical tests, and content analysis.

Keywords: Information Systems, Data Science, Computer Supported Cooperative Work, Social Computing

EDUCATION

Syracuse University, Syracuse, NY, USA 2023

Ph.D. Information Science and Technology GPA: 4.00/4.00

CAS, Data Science GPA: 4.00/4.00

Advisor: Prof. Kevin Crowston

Syracuse University, Syracuse, NY, USA 2018

M.S. Data Management GPA: 3.95/4.00

Advisor: Prof. Kevin Crowston

Thesis Topic: Sharing Open Deep Learning Models

Hacettepe University, Ankara, Turkey 2015

M.Sc., Science and Mathematics for Secondary Education GPA: 3.89/4.00

Thesis Topic: Evaluation of Teaching Practice Performance of Students of Secondary Mathematics Education by Using Fuzzy Logic

Hacettepe University, Ankara, Turkey

M.Sc., Mathematics (**Mastery of the field:** Abstract Algebra) 2014

Thesis Topic: D12 Modules and Rings characterized by D12 Modules GPA:
3.5/4.00

Anadolu University, Eskisehir, Turkey

2014

B.A, Business Administration (**with honors**)

Hacettepe University, Ankara, Turkey

2012

Education of Mathematics

(This is my undergraduate degree: combined 3.5 years **bachelor** in Mathematics and 1.5 years **master** in Education (**with honors**). This program was in **German**.)

REFERRED PUBLICATIONS

Journal

1. **Ocal, A.**, Crowston, K. (2023). Technological Frames: Discerning Public Interpretations about the Futures of Work with Intelligent Machines. *Information Technology & People (Q1 journal, under review)*.

2. **Öcal, A.**, Xiao, L, Park, J. (2021). Reasoning in social media: Insights from Reddit “Change My View”. *Online Information Review (Q1 journal, published)*.

Conference Papers

3. **Ocal, A.** (2023). Public Feelings About the future of AI: An Emotion Detection and Sentiment Analysis Approach Using BERT. *IEEE BlackSeaCom 2023*.

4. **Ocal, A.** (2023). Public Perceptions about AI Ethics. *IEEE 2023 Ethics*.

5. **Dalgali, A.** & Crowston, K. (2020). Algorithmic Journalism and Its Impacts on Work. In *Computation + Journalism Symposium*.

- 6. Dalgali, A. & Crowston, K. (2020).** Factors Influencing Approval of Wikipedia Bots. In *Proceedings of the 53rd Hawai'i International Conference on System Sciences (HICSS-53)*.
- 7. Dalgali, A. & Crowston, K. (2019).** Sharing Open Deep Learning Models. In *Proceedings of the 52nd Hawai'i International Conference on System Sciences (HICSS-52)*.
- 8. Öcal, A. & Turanlı, N. (2017).** Evaluation of Teaching Practice Performance of Students of Secondary Mathematics Education by Fuzzy Logic. In: Erçetin Ş., Potas N. (eds) Chaos, Complexity and Leadership 2017. ICCLS 2017. *Springer Proceedings in Complexity*. Springer, Cham.

Abstracts for Conferences

9. Dalgali, A. & Crowston, K. (2020). Algorithmic Journalism and Its Impacts on Work. International Conference on Information Systems (ICIS) PDW (Professional Development Workshops) on Artificial Intelligence – Beyond the Hype, and Pre-JASIST Workshop.

10. Dalgali, A. (2019). Factors Influencing Approval of Wikipedia Bots. 2nd WAIM Convergence Conference on the theme *At the Boundary: Exploring Human-AI Futures in Context*, 14-15 August 2019, Syracuse University.

11. Ocal, A. (2017). Poster Presentation. Evaluation of Prospective Mathematics Teachers' Performance by Using Fuzzy Logic. 2017 Grad Cohorts Computing Research Association (CRA)-Women Workshop, Washington.

12. Öcal, A. & Turanlı, N. (2015). Evaluation of Teaching Practice Performance of Students of Secondary Mathematics Education by Using Fuzzy Logic, *International Conference on Quality in Higher Education (ICQH 2015)*, Sakarya University, Sakarya, Turkey.

MASTERS THESES

1. Dalgali, A. (2018). Open Deep Learning Models. *Master Thesis*, M.S., Information Management (CAS: Data Science).

2. Öcal, A. (2015). Evaluation of Teaching Practice Performance of Students of Secondary Mathematics Education by Using Fuzzy Logic. *Master Thesis*, M.Sc., Science and Mathematics for Secondary Education program.

3. Öcal, A. (2014). D12 Modules and Rings characterized by D12 Modules. *Master Thesis*, M.Sc., Mathematics program.

PRESENTATIONS

Dalgali, A. (2018). Poster Presentation. Sharing Open Deep Learning Models. 1st iSchool research day, Syracuse University.

Dalgali, A. (2018). 3-minute thesis competition, Syracuse University.

RESEARCH EXPERIENCE

PROJECTS

Graduate Assistant for Work and AI project with Prof. Kevin Crowston
National Science Foundation (NSF). 2019-2020

2018-2019

Graduate Assistant for Argumentation Mining Project with Dr. Lu Xiao

National Science Foundation (NSF).

2017-2018

Research Assistant for FLOSS Project with Prof. Kevin Crowston

National Science Foundation (NSF), Cyber-Human Systems (CHS)

Small: Supporting stigmergic.

TEACHING EXPERIENCE

Syracuse University, 2021-2023 Instructor for the lab of IST 687 Introduction to Data Science (Graduate level)

Syracuse University, 2021-2022 Instructor for the lab of IST 387 Introduction to Data Science (Undergraduate level)

Syracuse University, 2020 Teaching Assistant for Statistical Methods in Information Science and Technology (Ph.D. course)

Syracuse University, 2017-2018 Teaching Assistant for System Analysis and Design Class

Syracuse University, 2017-2018 Tutor for Mathematics Classes

Frauliblings Gymnasium (Germany), 2012 Teaching practicum (as an undergraduate Erasmus student under the supervision of Prof. Martin Winter at Vechta University (Universität Vechta)).

AWARDS & SCHOLARSHIPS

Outstanding Teaching Assistant Award, 2023

IEEE Student Volunteer, 2023

Dissertation Award (Based on the dissertation proposal), Summer 2022

Certificate in University Teaching Recognition/Award, 2022

SIGCHI Student Full Travel Grant for CHI 2020

Computing Research Association (CRA)-Women Full Travel Grant for CRA-Women Workshop 2019

Computing Research Association (CRA)-Women Full Travel Grant for CRA-Women Workshop 2017

i-Prize Business Plan Competition Award, 2017 (One of the top two standout companies in Clean Tech track and \$500 to implement the idea)

German Academic Exchange Service (DAAD), Full Scholarship for the Summer 2013 (German Academic Exchange Service) Scholarship for an intensive German language course in Leibzig)

European Union Student Exchange Program Erasmus Scholarship, Spring 2012

PROFESSIONAL ASSOCIATIONS

IEEE Graduate Student Membership, 2023

FPP_Wise member, 2020-present

Member of the AIS (Association of Information Systems), 2020-present

ACM e board-member, 2019-2020

ACM Vice Chair of Syracuse Chapter, 2019-2020

Professional member of the ACM (Association of Computing Machinery), 2017-present

ACM Communication Chair of Syracuse Chapter, 2017-2018

TSA (Turkish Student Association) at Syracuse University Membership, 2016-present

SERVICE

Reviewer

Conference on International Conference on Information Systems (ICIS) – 2020

Hawaii International Conference on System Sciences (HICSS) – 2020

European Conference on Information Systems (ECIS) – 2020